

General Disclaimer

One or more of the Following Statements may affect this Document

- This document has been reproduced from the best copy furnished by the organizational source. It is being released in the interest of making available as much information as possible.
- This document may contain data, which exceeds the sheet parameters. It was furnished in this condition by the organizational source and is the best copy available.
- This document may contain tone-on-tone or color graphs, charts and/or pictures, which have been reproduced in black and white.
- This document is paginated as submitted by the original source.
- Portions of this document are not fully legible due to the historical nature of some of the material. However, it is the best reproduction available from the original submission.

E84-10042

CR-171 715
C.1

AgRISTARS

"Made available under NASA sponsorship
in the interest of early and wide dis-
semination of Earth Resources Survey
Program information and without liability
for any use made thereof."

SR-K3-04438

A Joint Program for
Agriculture and
Resources Inventory
Surveys Through
Aerospace
Remote Sensing

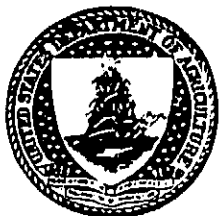
Supporting Research

AUGUST 1983

A SIMULATION STUDY OF SCENE CONFUSION FACTORS IN SENSING SOIL MOISTURE FROM ORBITAL RADAR

M. C. DOBSON, S. MOEZZI, R. ROTH
F. T. ULABY, PRINCIPAL INVESTIGATOR

REMOTE SENSING LABORATORY
THE UNIVERSITY OF KANSAS CENTER FOR RESEARCH, INC.
LAWRENCE, KANSAS



Lyndon B. Johnson Space Center
Houston, Texas 77058

(E84-10042) A SIMULATION STUDY OF SCENE
CONFUSION FACTORS IN SENSING SOIL MOISTURE
FROM ORBITAL RADAR Final Report (Kansas
Univ. Center for Research, Inc.) 138 p
HC A07/MF A01

N84-13635

Unclas
00042

CSCI 08M G3/43

| | | | | | |
|--|--|--|----------------------------|---|--|
| 1. Report No. SR-K3-04438 | | 2. Government Accession No. | | 3. Recipient's Catalog No. | |
| 4. Title and Subtitle A SIMULATION STUDY OF SCENE CONFUSION FACTORS IN SENSING SOIL MOISTURE FROM ORBITAL RADAR | | | | 5. Report Date August 1983 | |
| | | | | 6. Performing Organization Code | |
| 7. Author(s) M. C. Dobson, S. Moezzi, F. T. Ulaby, and E. Roth | | | | 8. Performing Organization Report No. RSL 601-1 | |
| 9. Performing Organization Name and Address Remote Sensing Laboratory University of Kansas Center for Research, Inc. 2291 Irving Hill Drive - Campus West Lawrence, Kansas 66045-2969 | | | | 10. Work Unit No. | |
| | | | | 11. Contract or Grant No. NCC 9-6 | |
| | | | | 13. Type of Report and Period Covered Final Report | |
| 12. Sponsoring Agency Name and Address Dale Browne NASA/Johnson Space Center Houston, Texas 77058 | | | | 14. Sponsoring Agency Code | |
| | | | | | |
| 15. Supplementary Notes | | | | | |
| 16. Abstract <p>Simulated C-band radar imagery for a 124-km by 108-km test site in eastern Kansas is used to classify soil moisture. Simulated radar resolutions are 100 m by 100 m, 1 km by 1 km, and 3 km by 3 km; all images are processed with greater than 23 independent samples. The simulated radar operates at 4.75 GHz with HH polarization and over 7° and 17° angles of incidence.</p> <p>Distributions of actual near-surface soil moisture are established daily for a 23-day accounting period using a water budget model dependent upon precipitation, potential evaporation, crop-canopy cover, crop development stage, surface slope, antecedent soil moisture, and soil hydrologic properties. Within the 23-day period, three orbital radar overpasses are simulated roughly corresponding to generally moist, wet, and dry soil moisture conditions. The radar simulations are performed by a target/sensor interaction model dependent upon a terrain model, land-use classification, and near-surface soil moisture distribution. Rayleigh fading, layover, and shadow are accounted for by the model. For each overpass date and each radar resolution, the received power and range position of a given pixel is used to classify near-surface soil moisture via a generalized algorithm requiring no ancillary data about scene characteristics.</p> <p>The accuracy of soil-moisture classification is evaluated for each single-date radar observation and also for multi-date detection of relative soil moisture change. In general, the results for single-date moisture detection show that 70% to 90% of cropland can be correctly classified to within +/- 20% of the true percent of field capacity. For</p> | | | | | |
| 17. Key Words (Suggested by Author(s)) Radar, Soil Moisture, Orbital, Simulation, Classification | | | 18. Distribution Statement | | |
| 19. Security Classif. (of this report) Unclassified | | 20. Security Classif. (of this page) Unclassified | | 21. No. of Pages 127 | |
| | | | | 22. Price* | |

Abstract continued:

a given radar resolution, the expected classification accuracy is shown to be dependent upon both the general soil moisture condition and also the geographical distribution of land-use (field-size distribution and dispersion of categories) and topographic relief. An analysis of cropland, urban, pasture/rangeland, and woodland subregions within the test site indicates that multi-temporal detection of relative soil moisture change is least sensitive to classification error resulting from scene complexity and topographic effects.

The 100 m by 100 m radar resolution is found to yield the most robust classification results, and it is concluded that further degradation of image resolution should be implemented in post-detection processing when and where coarse resolution analysis is warranted.

TABLE OF CONTENTS

| | Page |
|--|------|
| LIST OF FIGURES. | ii |
| LIST OF TABLES | v |
| ABSTRACT | vi |
| 1.0 INTRODUCTION. | 1 |
| 2.0 TEST-SITE DATA BASE | 4 |
| 2.1 Terrain Model and Radar Backscattering Categories | 6 |
| 2.2 Dynamics of Soil Moisture Distribution | 12 |
| 3.0 RADAR IMAGE GENERATION. | 17 |
| 4.0 SOIL MOISTURE CLASSIFICATION. | 38 |
| 4.1 Single Date Soil-Moisture Classification Accuracy | 41 |
| 4.2 Multidate Change Detection of Soil Moisture. | 62 |
| 5.0 CONCLUSIONS | 81 |
| 6.0 ACKNOWLEDGMENTS | 83 |
| REFERENCES | 84 |
| APPENDIX A | 86 |

LIST OF FIGURES

| | Page |
|---|------|
| Figure 1. Flowchart of simulation approach. | 5 |
| Figure 2. Digital terrain data of the test site showing the positions of the four subregions. | 7 |
| Figure 3. Land-use and crop-category distributions on Julian day 141 | 13 |
| Figure 4. Map of soil associations for test site. | 15 |
| Figure 5. Image presentation of the areal distribution of rainfall within the test site on each Julian date | 16 |
| Figure 6. Distribution of 0-5 cm soil moisture across the test site. Black represents undefined (zero) soil moisture | 18 |
| Figure 7. Cumulative distributions of soil moisture on satellite overpass dates. | 22 |
| Figure 8. Radar backscattering σ^0 at 4.75 GHz with HH polarization as a function of local incidence angle for selected moisture conditions. | 25 |
| Figure 9. Simulated radar imagery of the test site on Julian day 141. | 28 |
| Figure 10. Simulated radar imagery of the test site on Julian day 150. | 31 |
| Figure 11. Simulated radar imagery of the test site on Julian day 160. | 33 |
| Figure 12. Enlargements of the northwest corner of the simulated 100 m by 100 m resolution radar imagery on each overpass date | 36 |
| Figure 13. Near-surface soil moisture as estimated for Julian day 141 from simulated radar imagery with a 100 m by 100 m resolution | 40 |
| Figure 14. Soil moisture classification error E_m on Julian day 141 within the woodland subregion resulting from use of the "blind" classifier on 100 m by 100 m radar imagery. | 43 |
| Figure 15. Soil moisture classification error E_m resulting from each radar resolution for all moisture dependent pixels in the test site (excluding | |

| | | |
|------------|---|----|
| | woods) on a) Julian day 141, b) Julian day 150, and c) Julian day 160 | 45 |
| Figure 16. | Cumulative percent area of all moisture dependent pixels in the test site (excluding woods) as a function of absolute moisture classification error for each radar resolution | 49 |
| Figure 17. | Distribution of the difference between actual and classified soil moisture for the subregions of the test site as computed from 100-m resolution radar imagery for Julian day 141. | 53 |
| Figure 18. | Cumulative percent area correctly classified as to soil moisture versus maximum classification error (only moisture-dependent grid cells are compared) | 56 |
| Figure 19. | Cumulative percent area of all moisture dependent pixels in each subregion as a function of absolute moisture classification error on Julian day 150 | 60 |
| Figure 20. | Cumulative percent area of all moisture dependent pixels in each subregion as a function of absolute moisture classification error on Julian day 160. | 61 |
| Figure 21. | Change in actual soil moisture between Julian days 150 and 160; medium gray indicates no change in soil moisture, bright areas indicate drying over the period, and black areas indicate an increase in soil moisture | 66 |
| Figure 22. | Predicted change in soil moisture between Julian days 150 and 160 based on multirate radar imagery | 68 |
| Figure 23. | Distributions of actual ΔM_{fs} and predicted $\hat{\Delta M}_{fs}$ change in soil moisture | 70 |
| Figure 24. | Spatial distribution of difference between actual change in soil moisture and that predicted from multirate radar observation | 72 |
| Figure 25. | Magnitude of error in estimates of relative soil moisture change as a function of test site area | 75 |
| Figure 26. | Percent of test site area wherein relative change in soil moisture is correctly classified versus magnitude of classification error | 76 |

Figure 27. Percent of each subregion wherein relative change
in soil moisture is correctly classified versus
magnitude of classification error 78

LIST OF TABLES

| | | Page |
|---------|--|------|
| Table 1 | Area Percent of Data Base Assigned to Each Target Class | 8 |
| Table 2 | Field-Size Distributions for the Agricultural Portions of the Land-Use Subregions | 10 |
| Table 3 | Relative Percent of County Cropland Devoted to a Given Crop or Pasture/Range [9,10] | 11 |
| Table 4 | Examples of Class Specific Empirical Backscatter Models Used in Radar Simulations at 4.75 GHz and HH Polarization | 23 |
| Table 5 | Percent of Moisture Variant Area Correctly Classified to Within +/-20 of True Soil Moisture ($ E_m \leq 20\%$) | 58 |
| Table 6 | Percent Area Correctly Classified to Within +/-20% of the True Change in Soil Moisture M from Julian Day 150 to Julian Day 160 | 82 |

A SIMULATION STUDY OF SCENE CONFUSION FACTORS IN
SENSING SOIL MOISTURE FROM ORBITAL RADAR

M. C. Dobson, S. Moezzi, F. T. Ulaby, and E. Roth
Remote Sensing Laboratory
University of Kansas Center for Research, Inc.
Lawrence, Kansas 66045-2969

ABSTRACT

Simulated C-band radar imagery for a 124-km by 108-km test site in eastern Kansas is used to classify soil moisture. Simulated radar resolutions are 100 m by 100 m, 1 km by 1 km, and 3 km by 3 km; all images are processed with greater than 23 independent samples. The simulated radar operates at 4.75 GHz with HH polarization and over 7° to 17° angles of incidence.

Distributions of actual near-surface soil moisture are established daily for a 23-day accounting period using a water budget model dependent upon precipitation, potential evaporation, crop-canopy cover, crop development stage, surface slope, antecedent soil moisture, and soil hydrologic properties. Within the 23-day period, three orbital radar overpasses are simulated roughly corresponding to generally moist, wet, and dry soil moisture conditions. The radar simulations are performed by a target/sensor interaction model dependent upon a terrain model, land-use classification, and near-surface soil moisture distribution. Rayleigh fading, layover, and shadow are accounted for by the model. For each overpass date and each radar resolution, the received power and range position of a given pixel is used to classify near-surface soil moisture via a generalized

algorithm requiring no ancillary data about scene characteristics.

The accuracy of soil-moisture classification is evaluated for each single-date radar observation and also for multi-date detection of relative soil moisture change. In general, the results for single-date moisture detection show that 70% to 90% of cropland can be correctly classified to within $\pm 20\%$ of the true percent of field capacity. For a given radar resolution, the expected classification accuracy is shown to be dependent upon both the general soil moisture condition and also the geographical distribution of land-use (field-size distribution and dispersion of categories) and topographic relief. An analysis of cropland, urban, pasture/rangeland, and woodland subregions within the test site indicates that multi-temporal detection of relative soil moisture change is least sensitive to classification error resulting from scene complexity and topographic effects.

The 100 m by 100 m radar resolution is found to yield the most robust classification results, and it is concluded that further degradation of image resolution should be implemented in post-detection processing when and where coarse resolution analysis is warranted.

1.0 INTRODUCTION

Simulation techniques have been employed to study the relationship between spatial resolution and the accuracy at which soil moisture can be estimated from orbital C-band radar imagery [1,2]. These studies were based upon the land-use and crop-canopy-cover distributions present within a relatively small agricultural test site (18 km x 19 km) adjacent to the Kansas River in eastern Kansas. Image simulation techniques were used to generate synthetic-aperture radar (SAR) images at a frequency of 4.75 GHz with HH polarization and with angles of incidence between 7° and 22° from nadir. SAR images were produced at three different spatial resolutions: 20 m by 20 m with 12 looks, 93 m by 100 m with 23 looks, and 1 km by 1 km with 230 looks. In addition, simulated real-aperture radar (RAR) imagery was produced with a spatial resolution of 2.6 km x 3.1 km with 363 looks. Analysis of these images demonstrated that for relatively flat agricultural portions of the test site about 90% of the 20-m by 20-m pixel elements can be correctly classified to within +/- 20 percent of field capacity using a generalized soil moisture algorithm. In general, moisture classification accuracy was found to be greatest for coarser resolution imagery due to the increased number of looks; however, the results also showed a distinct classification-accuracy dependence on the complexity of the "true" soil moisture distribution and also upon the spatial

distribution of land-use elements within the test site.

As a consequence, the current study is designed to examine further the effects of the spatial distribution of land-use categories, the agricultural field-size distribution, the crop-canopy mix, and the variability of local topographic relief on the soil-moisture classification accuracy achievable by various orbital radar resolutions at 4.75 GHz, HH polarization, and angles of incidence from 7° to 17°. An area of 124 km by 108 km, including most of the Lawrence, Kansas USGS quadrangle (1:250,000), serves as the test site. The area includes large subregions dominated by urban features, mixed cropland, rangeland and pasture, or deciduous woodland. Simulated radar imagery of this test site at resolutions of 100 m by 100 m, 1 km by 1 km, and 3 km by 3 km are used to classify soil moisture, which is subsequently compared to the input "true" soil moisture. Classification accuracies of each radar resolution are compared for the whole test site and also for each of four subregions related to different mixtures of land-use. Since the number of processed looks for all resolutions is large ($N \geq 23$), the relative classification accuracies of each resolution should be only minimally biased by fading statistics.

The dynamic behavior of each 100 m by 100 m grid cell within the simulation test site is modeled over a 23 day time period with respect to near surface soil moisture, crop canopy cover, crop stage-of-growth, and soil surface

roughness. The input parameters to this model include static conditions such as topography and soil association and also dynamic components consisting of cropping practices and daily meteorological conditions. The cropping parameters are based upon a stochastic treatment of average crop calendar, field size distribution, and crop development while the meteorological data includes daily rainfall and potential evaporation. The output of this model consists of daily updates of near surface (0-5 cm) soil moisture and radar backscatter category which is approximately equivalent to a Level III land-use category [3]. The model is run for a 23 day period and the outputs are saved on 3 dates corresponding to hypothetical orbital overpasses each nine days apart. The overpass dates were selected independent of any consideration of orbital mechanics but rather to represent three distinctive soil moisture distributions over the test site: very wet, moist, and dry. The above moisture classifications are very general, however, since the large size of the data base and the late spring time frame of the simulations leads to highly variable regional soil moisture distributions on any given date.

For each orbital overpass, a target-sensor interaction model produces simulated radar imagery for each of the three radar resolutions. The simulation model accounts for the effects of Rayleigh fading and geometric properties such as layover and shadowing [22]. Each simulated radar image is then subjected to a generalized algorithm (requiring only the

amplitude of received power and the range position of a given pixel) which classifies the image into estimated soil moisture. These distributions of estimated soil moisture are subsequently compared with the distributions of actual near-surface soil moisture on a grid-cell basis for each date.

In addition to testing the absolute classification accuracies of each radar resolution for each of the three overpass dates in an instantaneous sense, multi-temporal data from two of the overpasses is used to evaluate the merits of relative change detection of near surface soil moisture as estimated from each of the three simulated radar resolutions. The above process is shown schematically in Figure 1.

2.0 TEST-SITE DATA BASE

In order to quantify the radar backscattering from a given terrain element, certain geometric and dielectric properties of the target scene must be known. First, the three-dimensional cartographic coordinates of each element must be specified relative to the orbital radar in order to compute range, area, and local incidence angle. Secondly, the radar backscattering category must be established; this is roughly equivalent to a level-III land-use classification category [3]. Finally, many land-use categories have backscattering properties that vary as a function of crop-canopy cover, row directionality, and near-surface soil

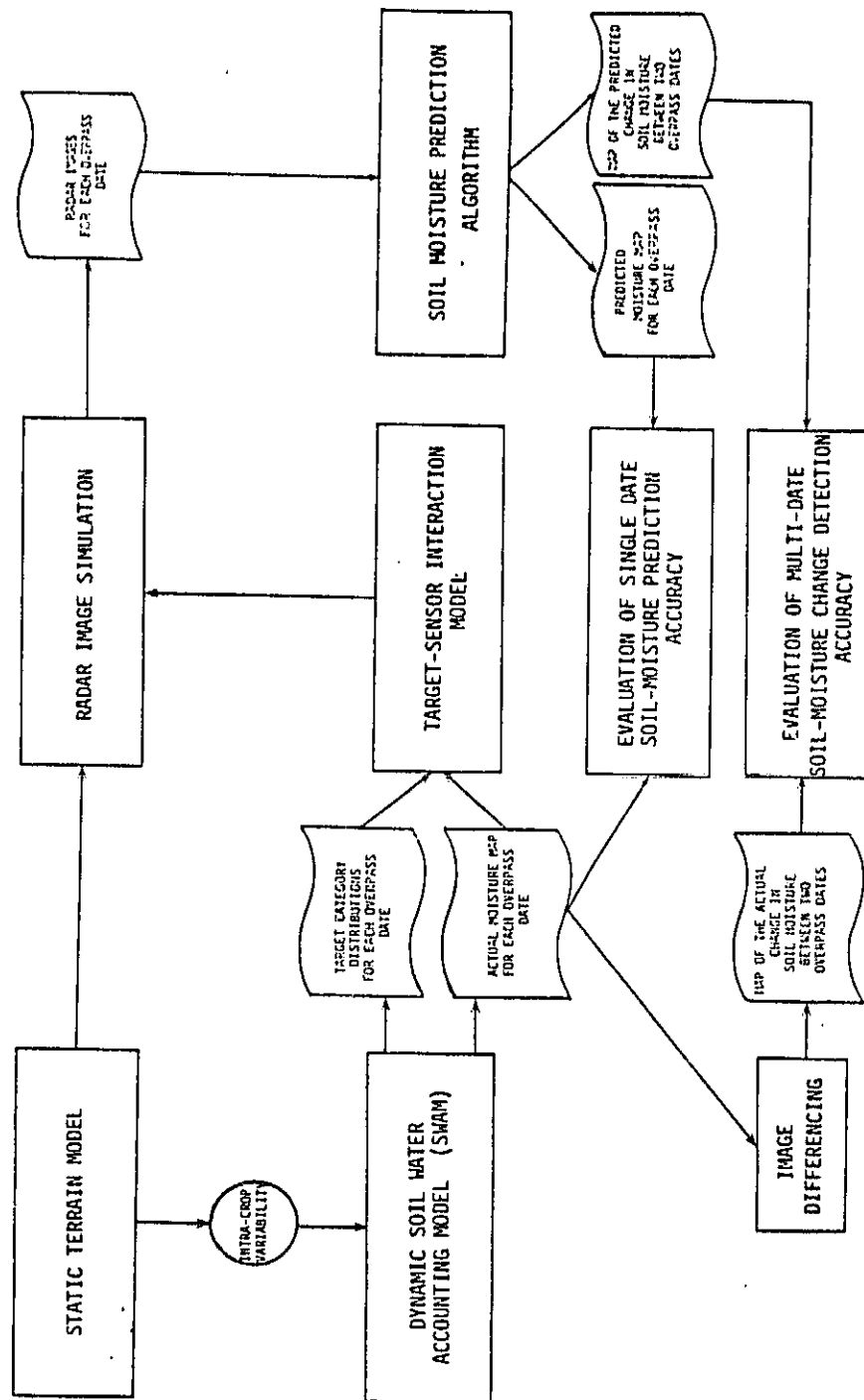


Figure 1. Flowchart of simulation approach.

moisture. A three-tiered digital data base is constructed to describe the spatial distribution of category elements and a dynamic model acts upon this distribution to vary target dielectric and backscattering properties as a function of time. It is assumed that all target properties are laterally homogeneous within a given 100 m by 100 m terrain element.

2.1 Terrain Model and Radar Backscattering Categories

Digital elevation data from the Defense Mapping Agency provide a static model of the terrain geometry. These data are corrected for scanning errors and resampled to yield a mean elevation for each 100-m by 100-m grid element within the 124-km by 108-km test site. An image-format presentation of the digital elevation data is shown in Figure 2.

The specification of radar backscattering category for each 100-m by 100-m grid element involves a three-step process that accurately describes the spatial distribution of the categories shown in Table 1 in a stochastic sense. A two-dimensional digital matrix of Level-II land-use classification is given by USGS land-use and land-cover digital data (LUDA) for the Lawrence, Kansas quadrangle. Level-II categories with similar radar backscattering properties (such as lakes and rivers) are redefined as equivalent backscattering categories. The Level-II LUDA category of cropland is insufficient to specify unique backscattering characteristics; thus a stochastic process is

ORIGINAL PAGE 13
OF POOR QUALITY

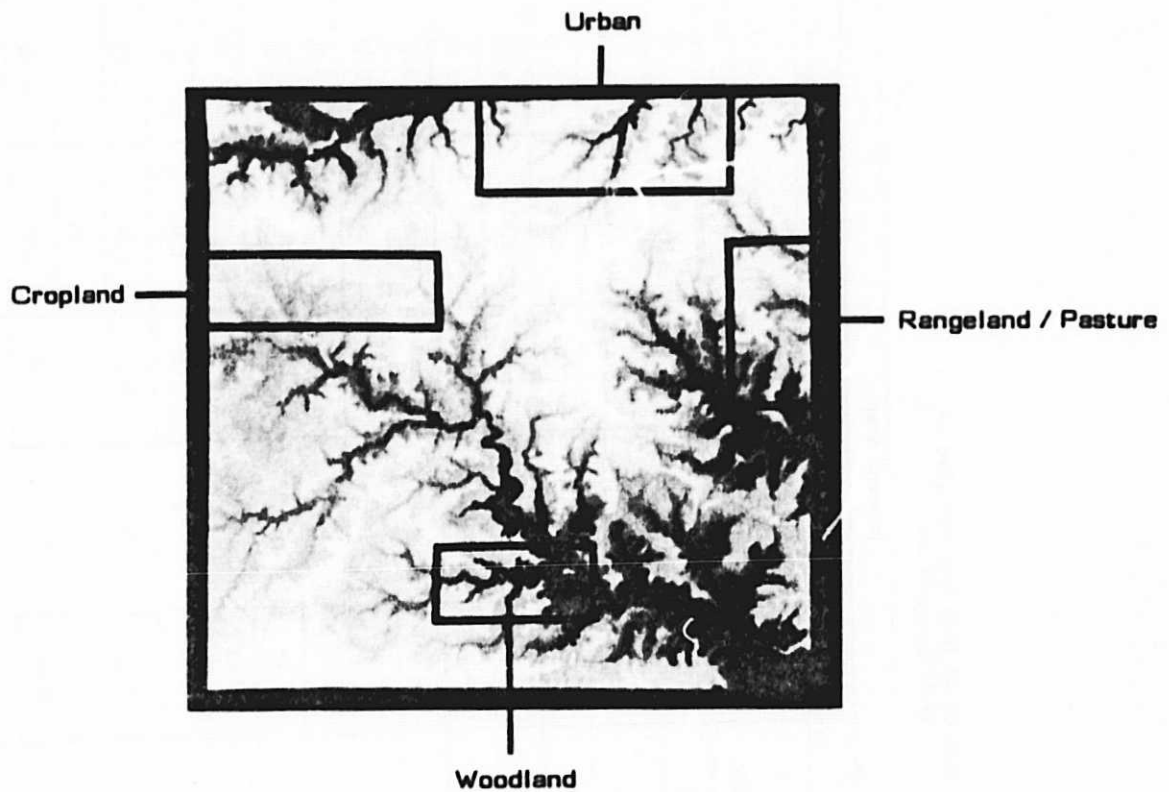


Figure 2. Digital terrain data of the test site showing the positions of the four subregions.

ORIGINAL REPORT
OF POOR QUALITY

TABLE 1. Area Percent of Data Base Assigned to
Each Target Class

| Backscattering Category | Percent Area | | | | | | |
|--|--------------------|----------|-------|-----------------------------|--------|---------|--------------------|
| | Whole Test Site | Day 141 | | | | Day 150 | Whole Test Site |
| | | Cropland | Urban | Rangeland and Pasture | Forest | | |
| Residential | 2.00 | 0.25 | 23.32 | 0.42 | 0.07 | 2.00 | 2.00 |
| Buildings (Commercial and Industrial) | 0.28 | 0.04 | 2.77 | 0.06 | 0.00 | 0.28 | 0.28 |
| Roads | 0.88 | 0.82 | 5.35 | 0.08 | 0.00 | 0.88 | 0.88 |
| Woodland (Deciduous) | 6.44 | 2.62 | 3.22 | 3.22 | 26.41 | 6.44 | 6.44 |
| Water | 1.71 | 0.03 | 0.12 | 0.12 | 13.25 | 1.49 | 0.53 |
| Smooth Bare Soil | 0.05 | 0.04 | 0.06 | 0.09 | 0.10 | 0.05 | 0.05 |
| Medium Rough Bare Soil* | 24.32 | 27.89 | 11.61 | 21.31 | 17.96 | 21.43 | 18.47 |
| Rough Bare Soil | 0.54 | 0.08 | 2.42 | 0.07 | 0.38 | 0.55 | 0.56 |
| Pasture / Rangeland | 48.61 | 50.83 | 36.77 | 61.53 | 30.24 | 48.61 | 49.30 |
| Wheat | 5.25 | 5.81 | 2.63 | 4.02 | 4.26 | 5.26 | 5.33 |
| Corn | 0.50 | 0.79 | 0.29 | 0.50 | 0.20 | 1.43 | 1.46 |
| Soybeans | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 1.36 | 2.63 |
| Sorghum | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.01 | 0.02 |
| Oats | 0.50 | 0.43 | 0.03 | 0.38 | 0.46 | 0.49 | 0.50 |
| Alfalfa | 8.92 | 10.37 | 4.77 | 8.23 | 6.67 | 8.93 | 9.06 |

*10% of corn, 0% of soybeans, and 0% of sorghum emergent on Julian day 141; non-emergent
cropland is classified as medium rough bare soil.

used to further define the spatial distribution of particular agricultural crops. A random sample of U-2 high-altitude color IR images is used to generate statistics on agricultural field-size distribution for each of the twelve counties within the test site. These statistics are then used to assign random field-boundary networks within each county. The distribution of field sizes is given by county in Table 2.

Specific crop categories and row directions are randomly assigned to each field within a county, based upon an historical enumeration of crop acreage for each county provided by the Kansas State Board of Agriculture and the Missouri Department of Agriculture. These acreages are given by county in Table 3. In addition, since all crops are not grown concurrently, crop calendar data [4] is used to factor planting and harvest into the time history of each field. Within a given crop, planting and crop-development stages established for this area are used to change a given field's backscatter category from bare soil to that of the crop after emergence in a stochastic fashion. The fields of each crop type are subdivided into ten subgroups each with a distinctive cropping history. Thus, the crop-type distribution will vary locally as a function of time within the 23 day simulation period. The land-use and crop-type distributions for the entire 124 km by 108 km test site are shown in Table 1 for each of the hypothetical orbital overpass dates. The simulation period runs from May 18

ORIGINAL PAGE IS
OF POOR QUALITY

TABLE 2. Field-Size Distributions for the Agricultural Portions
of the Land-Use Subregions

| Subregion | Percent of Agricultural Area | | | | | | | | | |
|---------------------|------------------------------|----|----|----|----|----|-----|-----|-----|-----|
| | Field Size in Acres | | | | | | | | | |
| | 10 | 20 | 30 | 40 | 60 | 80 | 100 | 120 | 140 | 160 |
| Urban (Kansas City) | 20 | 18 | 10 | 15 | 7 | 16 | 3 | 2 | 2 | 7 |
| Pasture/Rangeland | 4 | 11 | 6 | 18 | 8 | 28 | 3 | 5 | 3 | 14 |
| Cropland | 20 | 23 | 12 | 19 | 11 | 6 | 2 | 2 | 2 | 3 |
| Woodland | 20 | 23 | 12 | 19 | 11 | 6 | 2 | 2 | 2 | 3 |

TABLE 3. Relative Percent of County Cropland
Devoted to a Given Crop or Pasture/Range [9,10]

Group A = Anderson County

Group B = Bates, Douglas, Franklin, Linn, and Miami Counties

Group C = Cass, Jackson, and Johnson Counties

| Group | Percent of Total Agricultural Land | | | | | | |
|-------|------------------------------------|---------|------|------|----------|---------|------------------------|
| | Wheat | Sorghum | Corn | Oats | Soybeans | Alfalfa | Pasture Hay & Range |
| A | 8.6 | 7.4 | 5.7 | 0.5 | 21.1 | 13.7 | 43.0 |
| B | 6.3 | 9.6 | 5.5 | 0.5 | 15.2 | 10.3 | 52.0 |
| C | 4.1 | 5.2 | 5.8 | 0.4 | 11.6 | 8.2 | 64.7 |

Note: Urban Subregion consists of most of Jackson and Johnson Counties

Cropland Subregion consists of parts of Douglas, Franklin, Johnson,
and Miami Counties

Pasture/Rangeland Subregion consists of most of Cass County

Woodland Subregion consists of a large part of Linn County

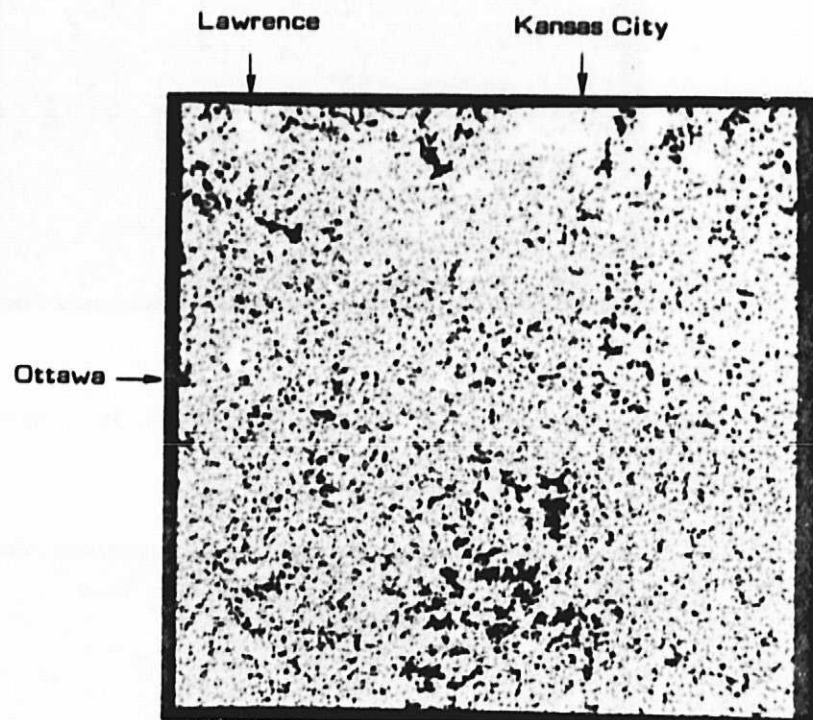
(Julian day 138) until June 9 (Julian day 160) during which time corn and soybeans are emerging and this is reflected in Table 1. Examples of land-use and crop-category distribution are shown in Figure 3 for Julian day 141.

2.2 Dynamics of Soil Moisture Distribution

The above two components of the data base define the geometric properties of the test site and the distribution of backscattering categories. In addition, it is necessary to model certain dynamic conditions that largely determine the dielectric properties of the scene elements. Of major importance is the near-surface soil moisture of each 100-m by 100-m pixel element as a function of time.

The soil moisture is governed by soil type, local slope, crop canopy cover and stage of growth, antecedent soil moisture, precipitation, and potential evaporation. The distribution of soil types as generalized by soil associations from USDA/SCS county soil surveys is shown in Figure 4. The local crop calendar is derived for this area from historical records [4] and used to establish the daily transpiration rate for a given crop. Daily weather records from each of 25 reporting stations are used to generate digital overlays of daily precipitation (Figure 5) and potential evaporation. A water-budget model is used to update near-surface soil moisture on a daily basis for each grid cell. Finally, a normally distributed random-noise

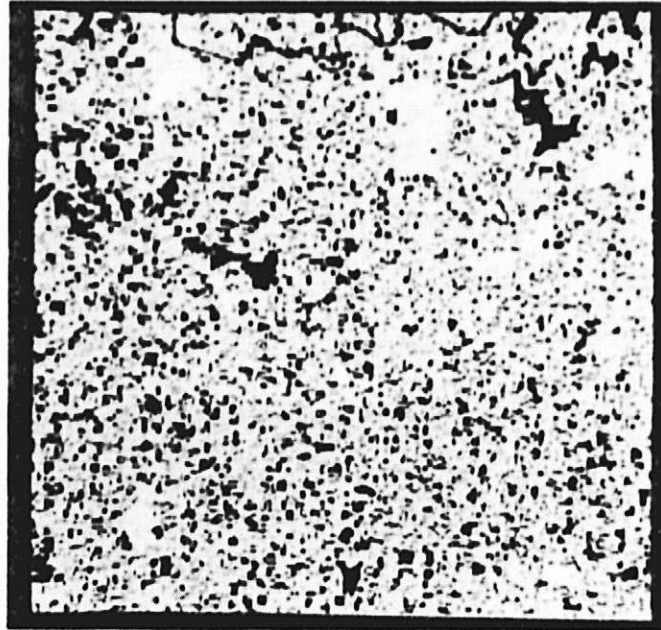
ORIGINAL PAGE IS
OF POOR QUALITY



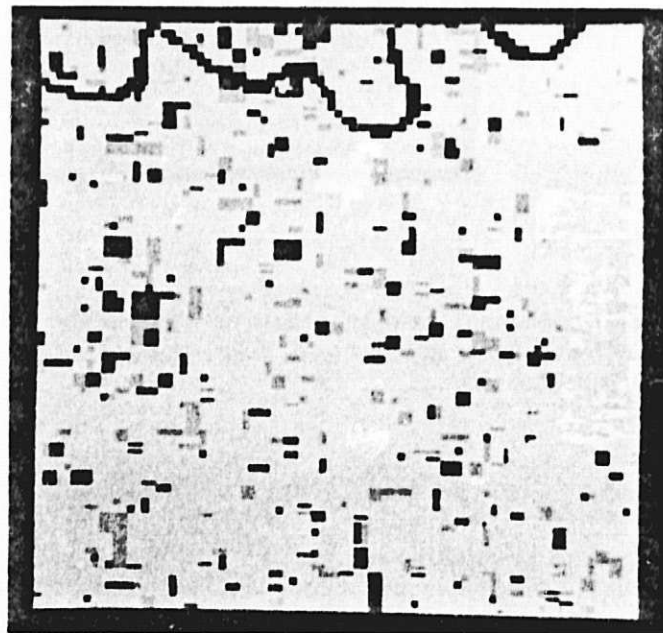
- (a) Land-use: urban features are bright while water and woods are darkest.

Figure 3. Land-use and crop-category distributions on Julian day 141.

ORIGINAL PAGE IS
OF POOR QUALITY



- (b) Enlargement of upper-left corner shows 51.2 km by 51.2 km of total scene.



- (c) Enlargement of 2b shows Kansas River and trees as black, urban features as white, the remainder of the image shows cropland of which soybeans are emphasized to show the presence of both north-south and east-west row directions.

ORIGINAL PAGE IS
OF POOR QUALITY



Figure 4. Map of soil associations for test site.

ORIGINAL PAGE IS
OF POOR QUALITY

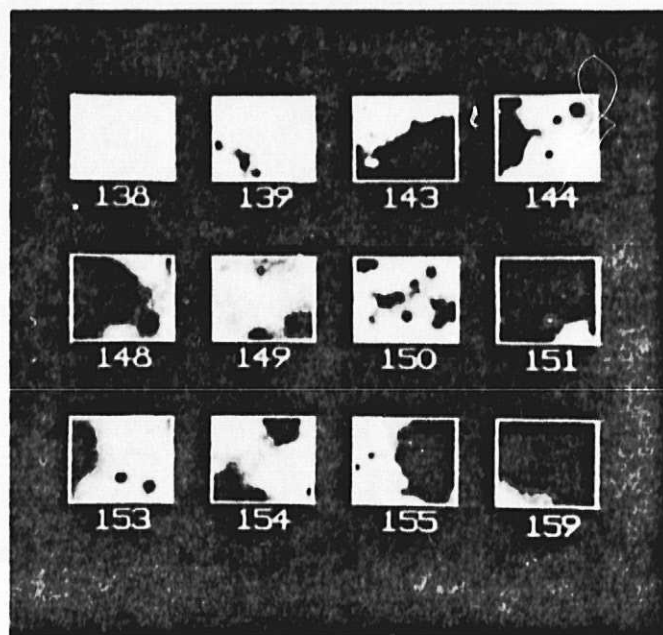


Figure 5. Image presentation of the areal distribution of rainfall within the test site on each Julian date.

component is added to the modeled soil moisture in order to simulate local, within-field variance in true soil moisture [2]. The details of the soil water accounting model and a listing of the computer program are given in Appendix A.

Examples of the 0-5 cm soil moisture distributions produced by the model are shown in Figure 6 for Julian days 141, 150, and 160 in image format. The corresponding cumulative areal distributions are shown in Figure 7a for each date. The influence of crop cover on soil moisture distribution is shown in Figure 7b for Julian day 150. These distributions when combined with the terrain model and the spatial distribution of radar backscatter categories collectively drive the radar image simulations discussed below.

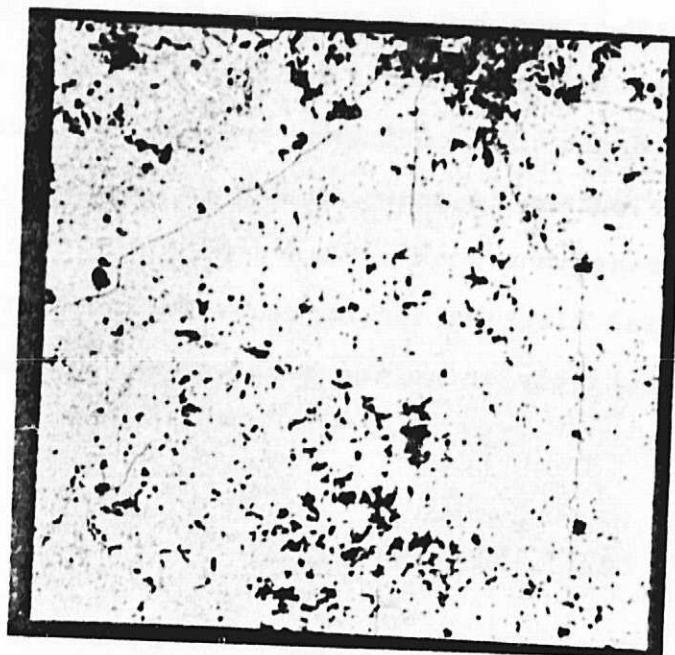
3.0 RADAR IMAGE GENERATION

The average return power \bar{P}_r reradiated from each laterally homogeneous grid cell is given by the radar equation

$$\bar{P}_r = \frac{P_T G^2 \lambda^2 \sigma^0 A}{(4\pi)^3 R^4} \quad (1)$$

where P_T is the average transmitted power, G^2 is the two-way antenna gain, λ is the wavelength, σ^0 is the radar cross section per unit area, A is the grid-cell area, and R is the range. For a given sensor configuration, P_T , G , and λ are

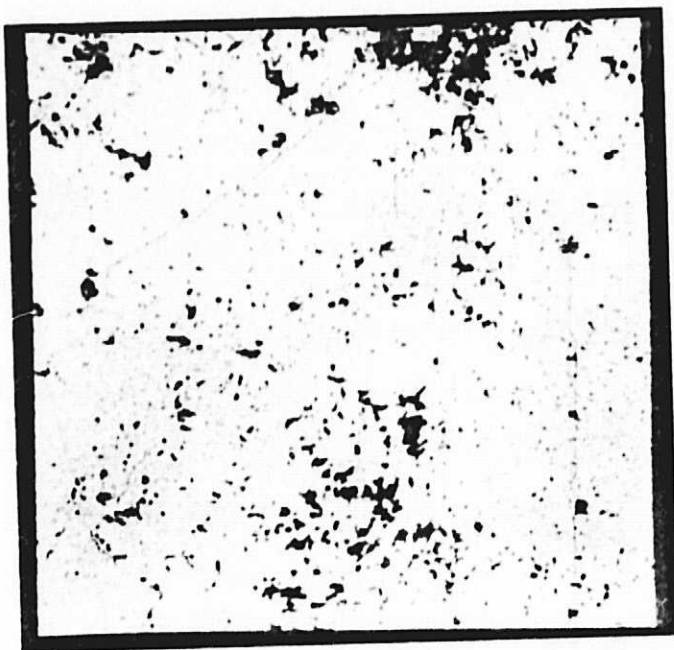
ORIGINAL PAGE IS
OF POOR QUALITY.



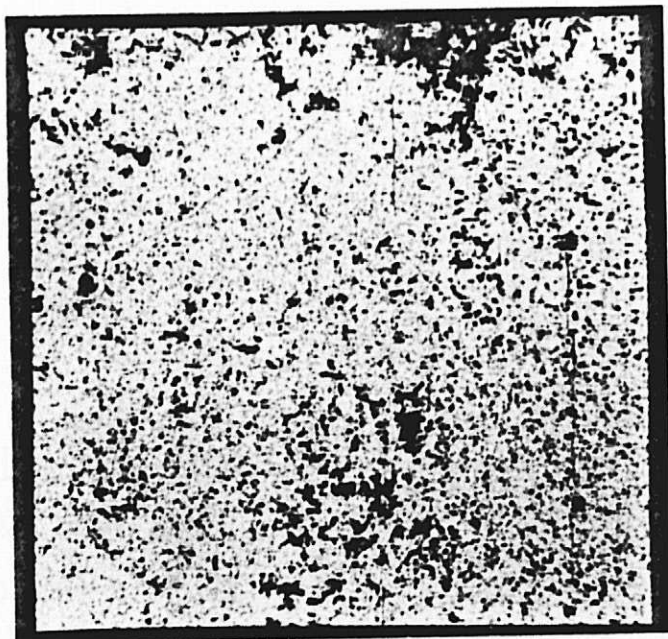
(a) Julian day 141.

Figure 6. Distribution of 0-5 cm soil moisture across the test site.
Black represents undefined (zero) soil moisture.

ORIGINAL PAGE 19
OF POOR QUALITY

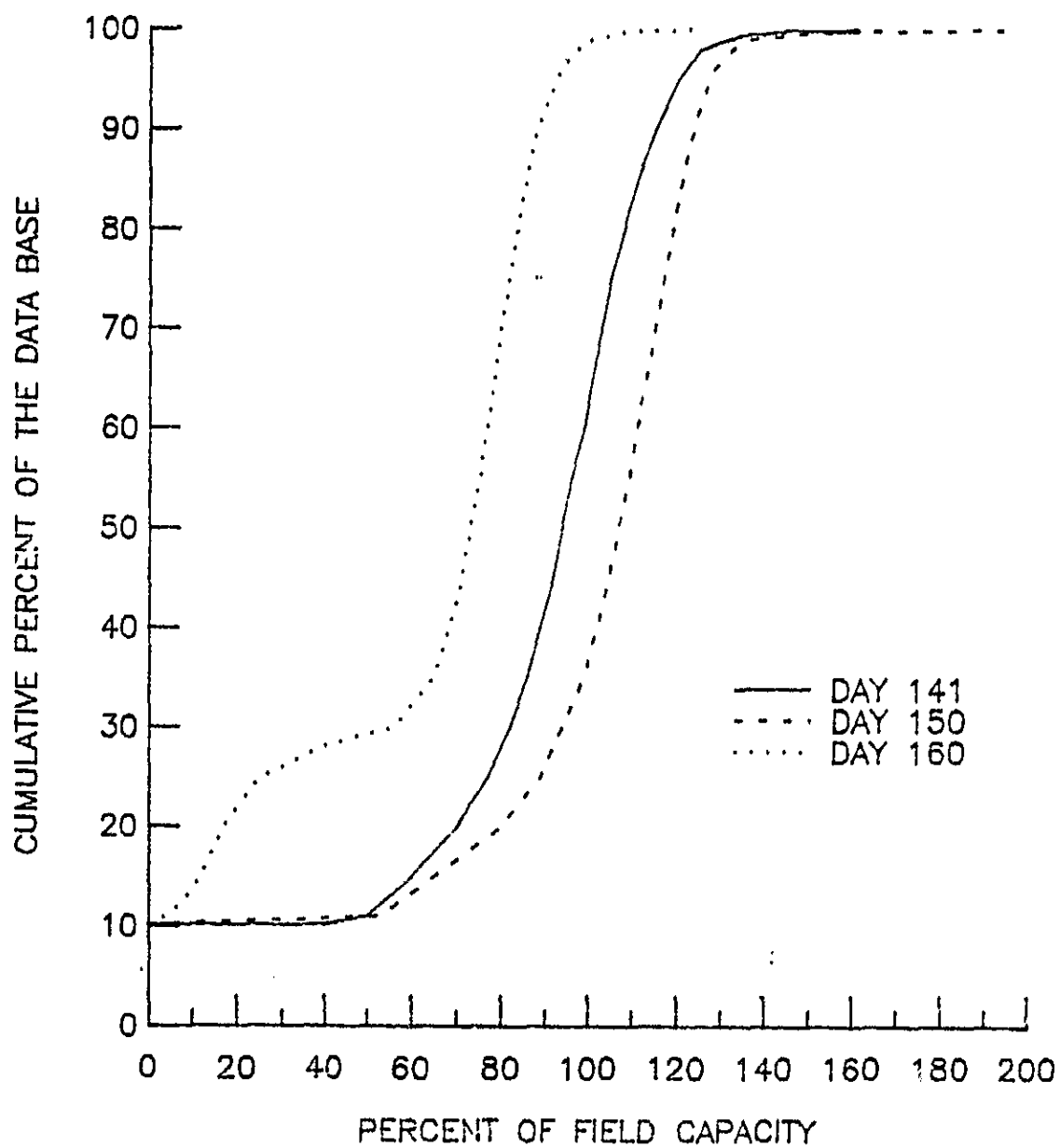


(b) Julian day 150.



(c) Julian day 160.

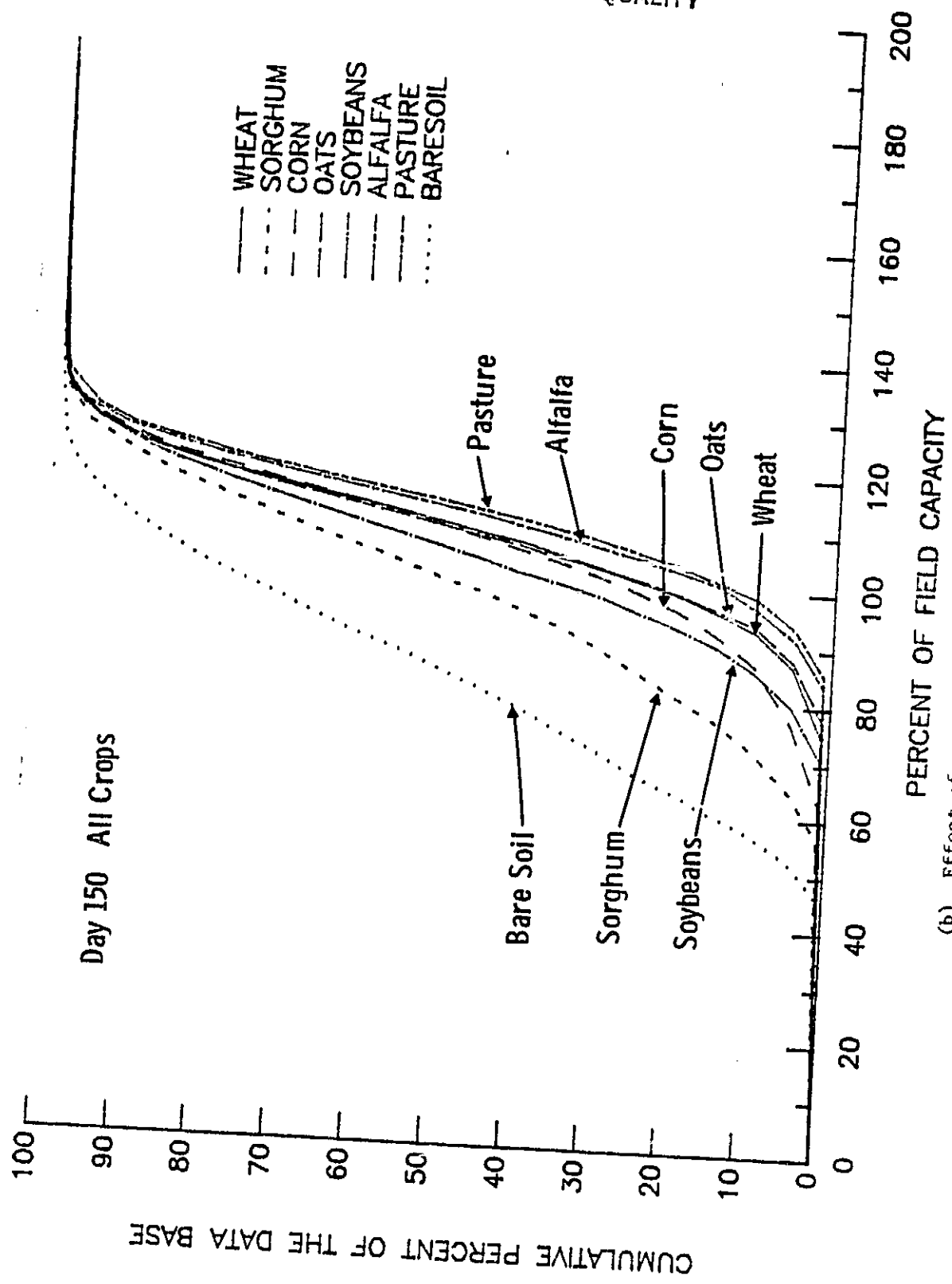
ORIGINAL PAGE IS
OF POOR QUALITY



(a) Net distribution for each date.

Figure 7. Cumulative distributions of soil moisture on satellite overpass dates.

ORIGINAL PAGE IS
OF POOR QUALITY



(b) Effect of crop canopy cover on Julian day 150.

constant. For each grid cell element, area and range are determined from the static terrain model. In addition, σ^0 varies as a function of local angle of incidence, backscattering category, and near-surface soil moisture; and for the purpose of radar simulation, σ^0 is given by empirical fits to experimental airborne and truck-mounted scatterometer data [6]. Examples of empirical radar backscatter dependence on target category, incidence angle and near-surface soil moisture are given in Table 4. Radar backscattering coefficient σ^0 is shown graphically in Figure 8 as a function of local incidence angle θ for selected categories and soil moisture conditions.

The power actually received at the antenna P_r is dependent upon signal fading and atmospheric scattering and adsorption. At 4.75 GHz the atmospheric losses are assumed to be negligible for most conditions. In addition, signal fading is assumed to be χ -square distributed with $2N$ degrees of freedom where N is the number of independent samples for a given range and azimuth radar resolution [7]. Hence,

$$P_r = \left(\frac{\bar{P}_r}{2N} \right) Y \quad (2)$$

where Y is a random variable with χ -squared distribution and $2N$ degrees of freedom.

The radar image simulation model accounts for the geometric effects of layover and shadowing. Examples of simulated orbital radar imagery are shown in Figure 9 for the

TABLE 4. Examples of Class Specific Empirical Backscatter Models
Used in Radar Simulations at 4.75 GHz and HH Polarization

A. Targets Modeled as a Function of Soil Moisture

| Target Class | Roughness Class or Row Direction | Algorithm Coefficients | | | | | | | |
|--------------|----------------------------------|------------------------|----------------|-----------------------------------|-----------------------------------|----------------|-----------------------------------|-----------------------------------|-----------------------------------|
| | | f(θ) | | | | g(θ) | | | |
| | | f ₁ | f ₂ | f ₃ × 10 ⁻² | f ₄ × 10 ⁻³ | g ₁ | g ₂ × 10 ⁻² | g ₃ × 10 ⁻³ | g ₄ × 10 ⁻⁵ |
| Wheat | NA | -1.932 | -2.000 | 9.336 | -1.287 | 0.114 | 0.931 | -0.914 | 1.575 |
| Milo | Parallel | -9.753 | -0.262 | 0.365 | -0.002 | 0.124 | -0.492 | 0.124 | -0.101 |
| Corn | Perpendicular | -9.753 | -0.246 | 0.865 | -0.169 | 0.124 | -0.492 | 0.125 | -0.101 |
| | Parallel | -7.748 | -0.395 | 0.281 | -0.054 | 0.129 | -0.330 | 0.409 | -0.029 |
| Soybeans | Perpendicular | -7.748 | -0.378 | 0.781 | -0.113 | 0.129 | -0.330 | 0.409 | -0.029 |
| | Parallel | -10.064 | -0.408 | 0.986 | -0.089 | 0.182 | -0.772 | 0.210 | -0.175 |
| Alfalfa | Perpendicular | -10.064 | -0.391 | 1.486 | -0.256 | 0.182 | -0.772 | 0.210 | -0.175 |
| | NA | -1.932 | -2.000 | 9.336 | -1.287 | 0.114 | 0.931 | -0.914 | 1.575 |
| Pasture | NA | -1.932 | -2.000 | 9.336 | -1.287 | 0.114 | 0.931 | -0.914 | 1.575 |
| Bare | Smooth | -5.191 | -1.556 | 4.617 | -0.477 | 0.182 | -0.163 | -0.085 | 0.205 |
| | Medium Rough | -11.705 | -0.434 | 0.767 | -0.033 | 0.137 | 0.282 | -0.231 | 0.366 |
| | Rough | -15.154 | 0.338 | -3.160 | 0.506 | 0.158 | -0.379 | 0.225 | -0.317 |

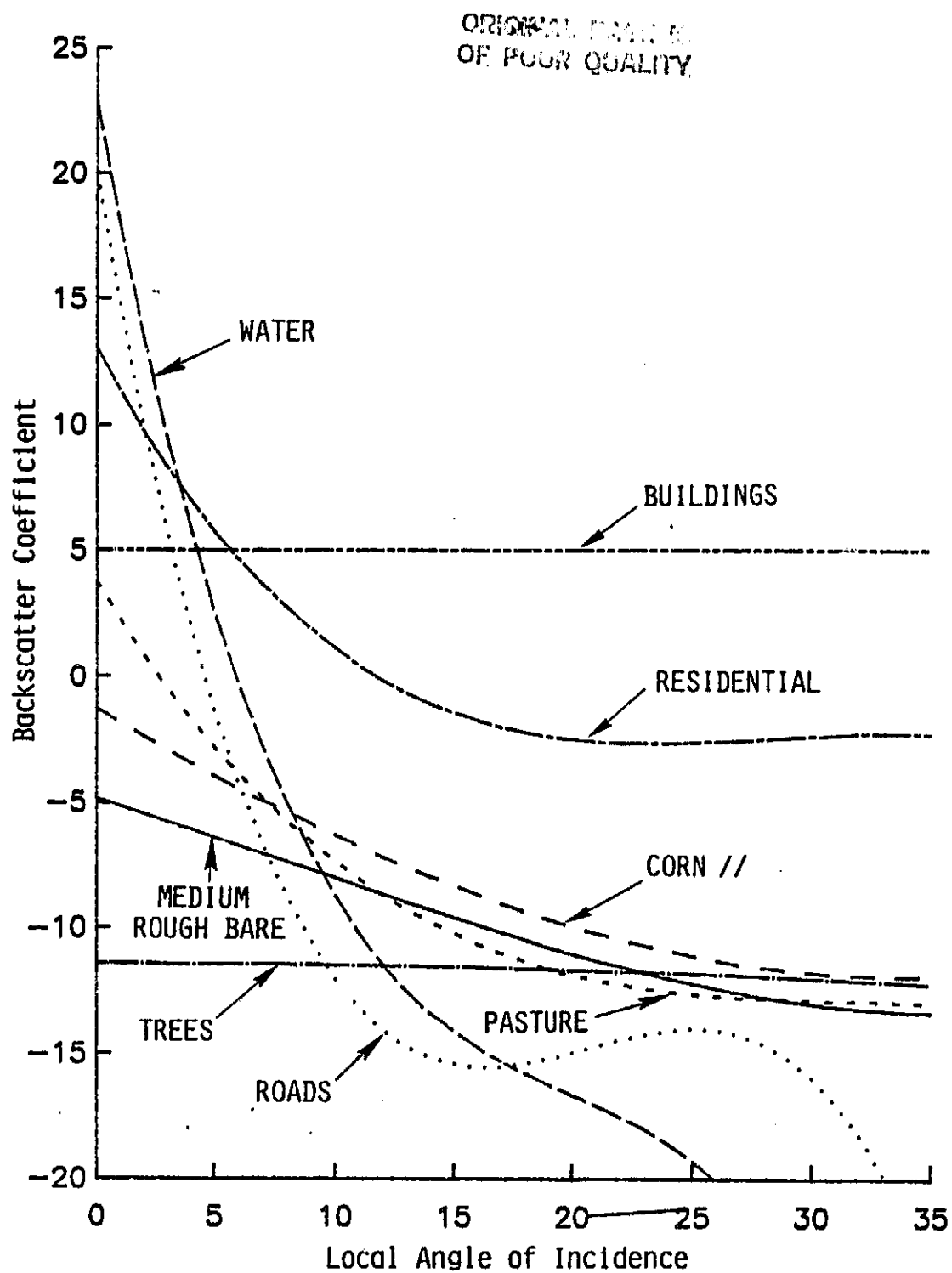
$$\sigma^0(\theta) = f(\theta) + g(\theta) M_{fs} \text{ for } \theta \leq 30^\circ$$

$$f(\theta) = f_1 + f_2\theta + f_3\theta^2 + f_4\theta^3$$

$$g(\theta) = g_1 + g_2\theta + g_3\theta^2 + g_4\theta^3$$

B. Targets Modeled with no Dependence on Soil Moisture

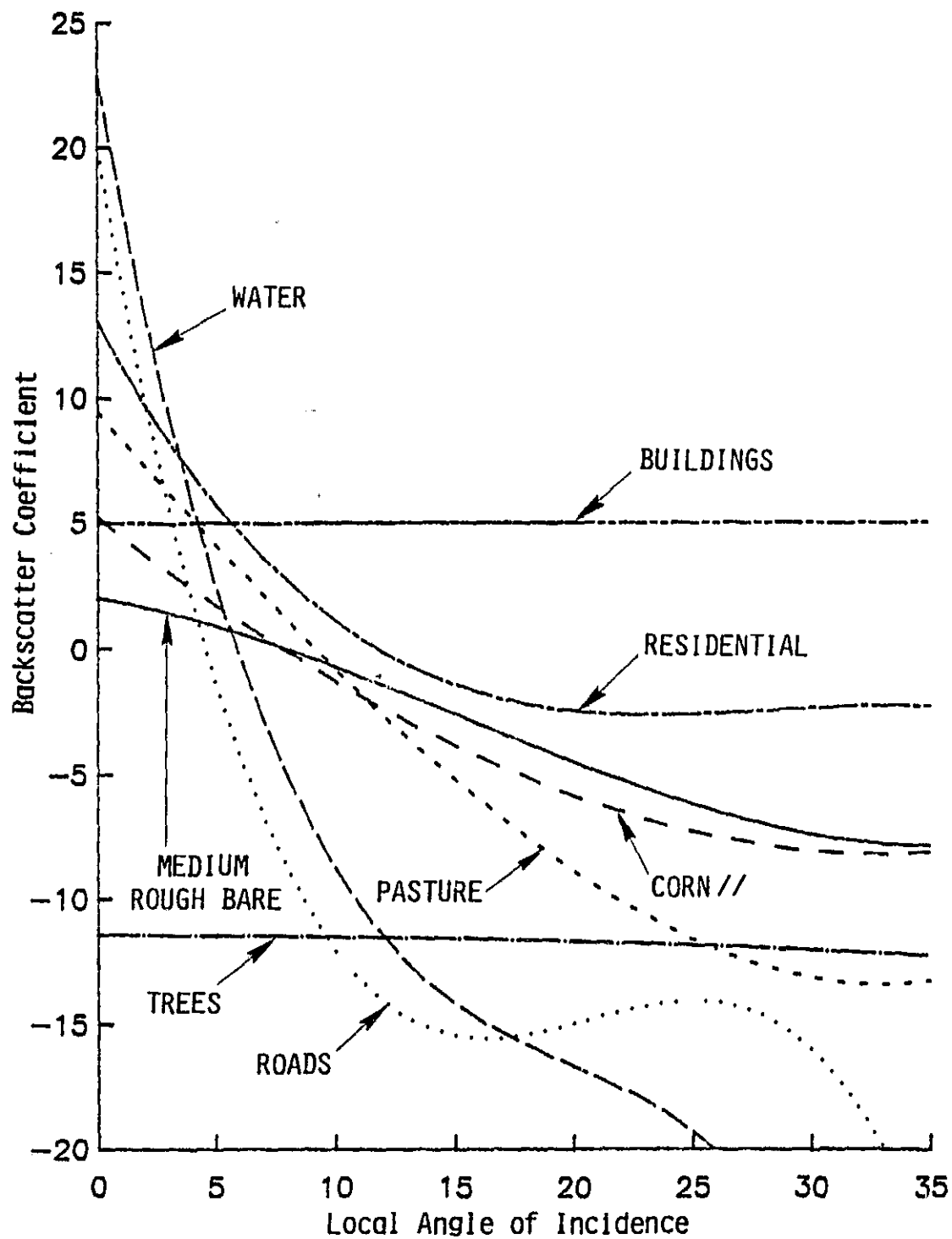
| Target Class | $f(\theta)$ |
|-------------------|--|
| Residential Areas | $13.019 - 1.755\theta + 0.640 \times 10^{-1} \theta^2 - 0.755 \times 10^{-3} \theta^3$ |
| Water Bodies | $22.820 - 5.126\theta + 2.370 \times 10^{-1} \theta^2 - 3.973 \times 10^{-3} \theta^3$ |
| Roads | $20.000 - 5.550\theta + 2.800 \times 10^{-1} \theta^2 - 4.500 \times 10^{-3} \theta^3$ |
| Deciduous Trees | $10 \log (10^{-1.143} \times \cos\theta)$ |
| Buildings | Constant value 5 dB |



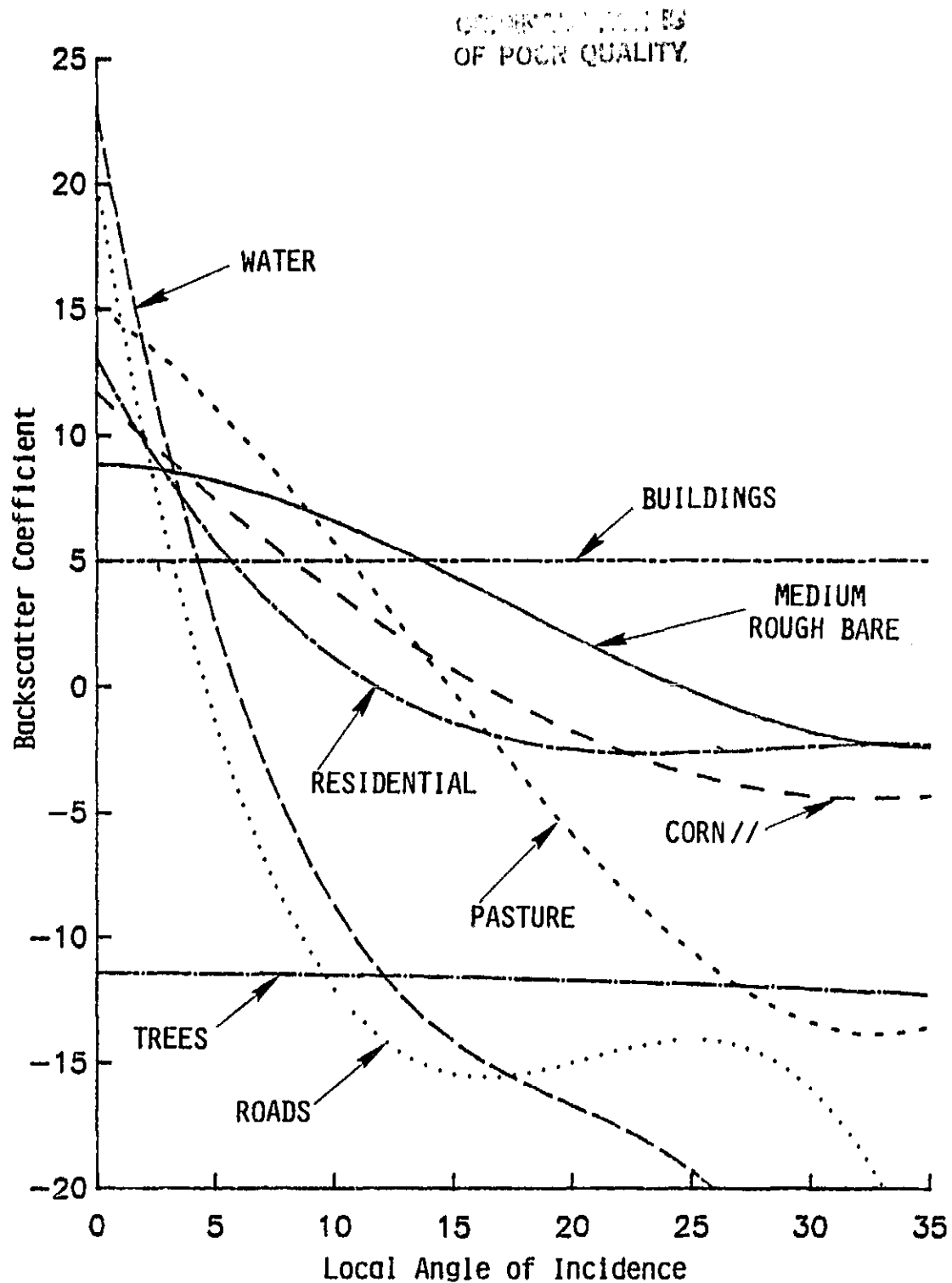
(a) Soil moisture is 50% of field capacity.

Figure 8. Radar backscattering σ^0 at 4.75 GHz with HH polarization as a function of local incidence angle for selected moisture conditions.

OF POOR QUALITY

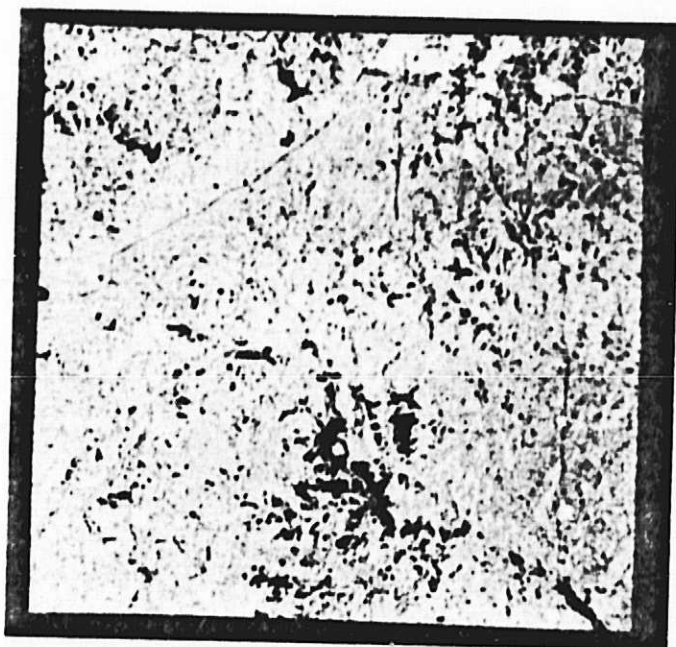


(b) Soil moisture is 100% of field capacity.



(c) Soil moisture is 150% of field capacity.

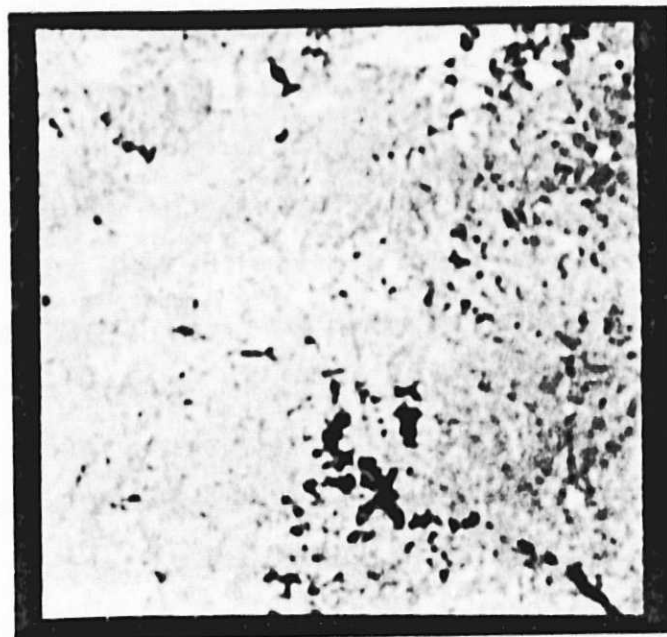
ORIGINAL PAGE IS
OF POOR QUALITY



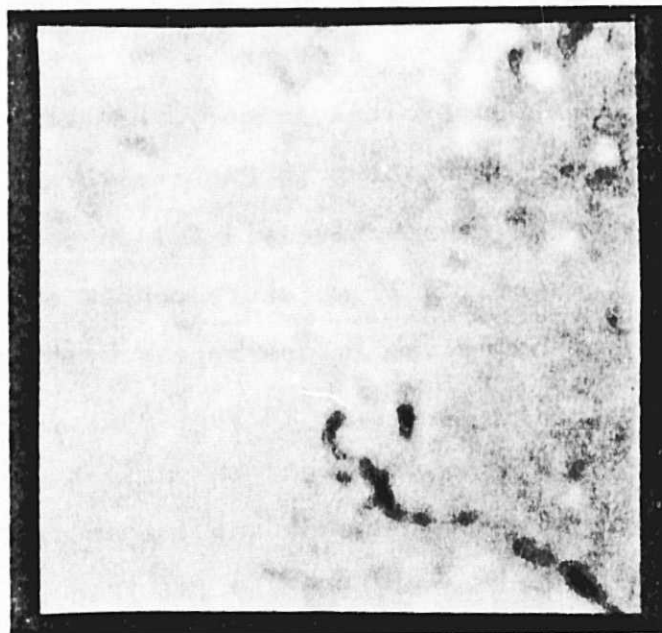
(a) 100 m by 100 m radar resolution.

Figure 9. Simulated radar imagery of the test site on Julian day 141.

ORIGINAL PAGE IS
OF POOR QUALITY



(b) 1 km by 1 km radar resolution.



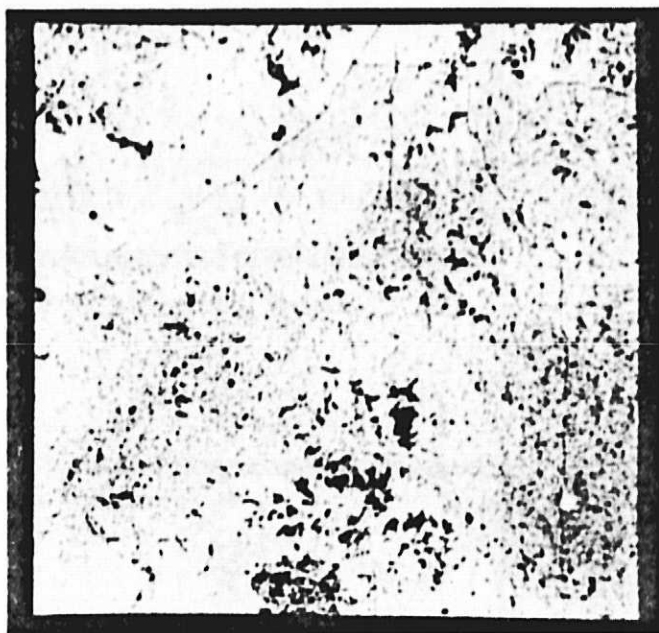
(c) 3 km by 3 km radar resolution.

soil moisture distribution present on Julian day 141 (Figure 5a) at radar resolutions of 100 m by 100 m, 1 km by 1 km and 3 km by 3 km. These images are ground-range presentations and P_r is scaled in dB to facilitate the presentation of the large dynamic range in P_r across the image swath (≈ 48 dB). The radar illumination is from the west (left side of images). Due to the relatively steep incidence angles ($7^\circ - 17^\circ$), the angular decay in P_r is readily apparent across the swath from left to right. In general, areas of higher near-surface soil moisture as related to antecedent precipitation appear brighter on the images, and this is most apparent as diagonal stripes related to storm tracks. Also, areas of tree canopy cover and water bodies tend to be dark on the imagery simulated for Julian day 141, while urban features tend to appear bright and are especially noticeable in the far range (right side of images).

The simulated orbital imagery for the three radar resolutions are also shown in Figures 10 and 11 for Julian days 150 and 160, respectively. Julian day 150 represents the wettest overall soil moisture conditions as indicated in Figure 7, and hence the images appear brighter than those for Julian day 141 (Figure 9). In contrast, Julian day 160 is shown by Figure 7 to represent the driest overall soil moisture conditions, and thus the images in Figure 11 appear darker than those for Julian day 141 (Figure 9).

It should be noted that for all of the above simulated images (Figures 9, 10, 11), the number of independent looks

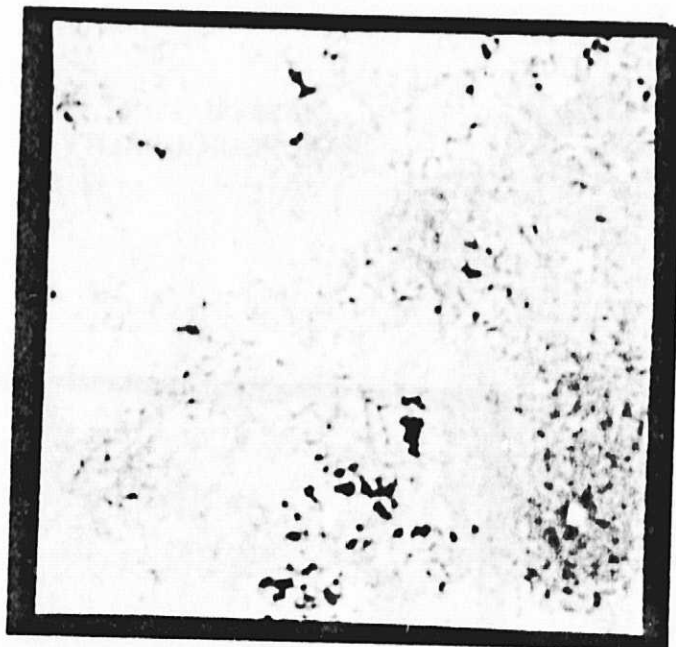
ORIGINAL PAGE IS
OF POOR QUALITY



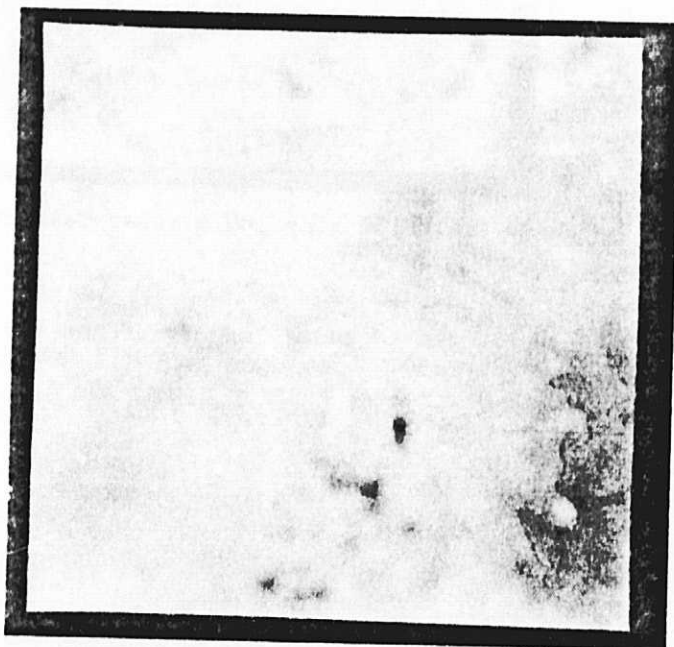
(a) 100 m by 100 m radar resolution.

Figure 10. Simulated radar imagery of the test site on Julian
day 150.

ORIGINAL PAGE IS
OF POOR QUALITY

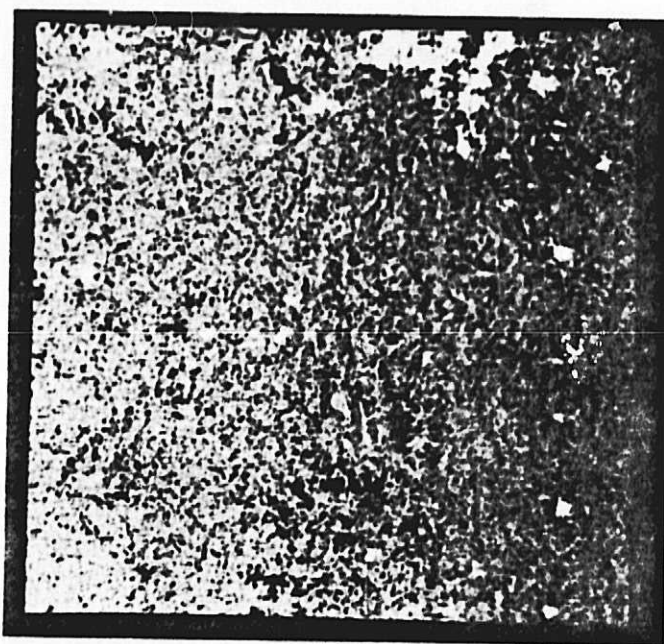


(b) 1 km by 1 km radar resolution.



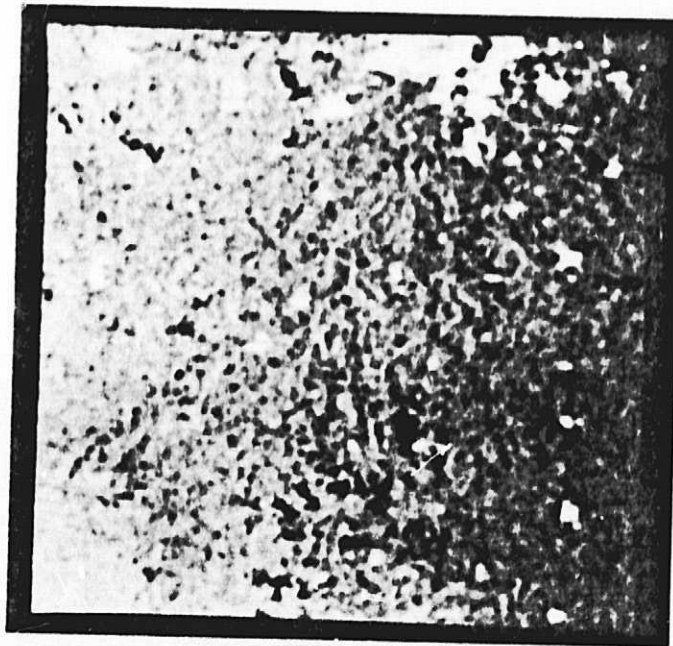
(c) 3 km by 3 km radar resolution.

ORIGINAL PAGE IS
OF POOR QUALITY

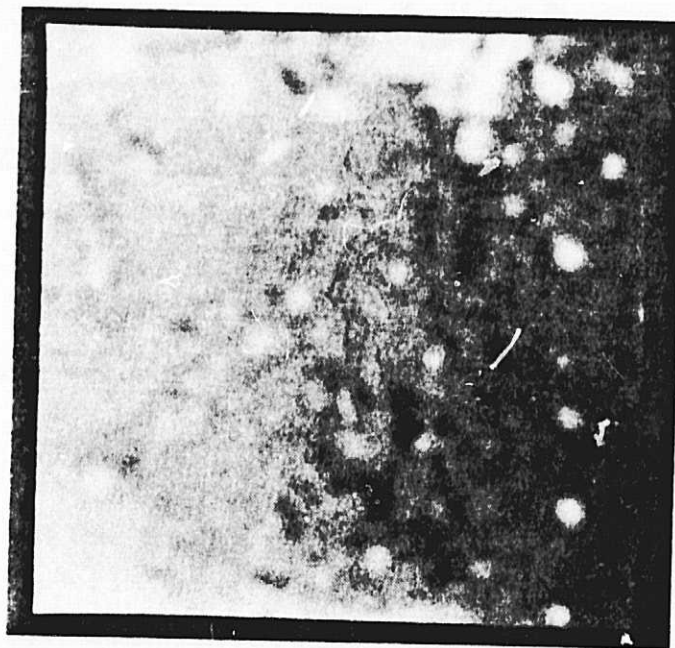


(a) 100 m by 100 m radar resolution.

Figure 11. Simulated radar imagery of the test site on Julian day 160.



(b) 1 km by 1 km radar resolution.



(c) 3 km by 3 km radar resolution.

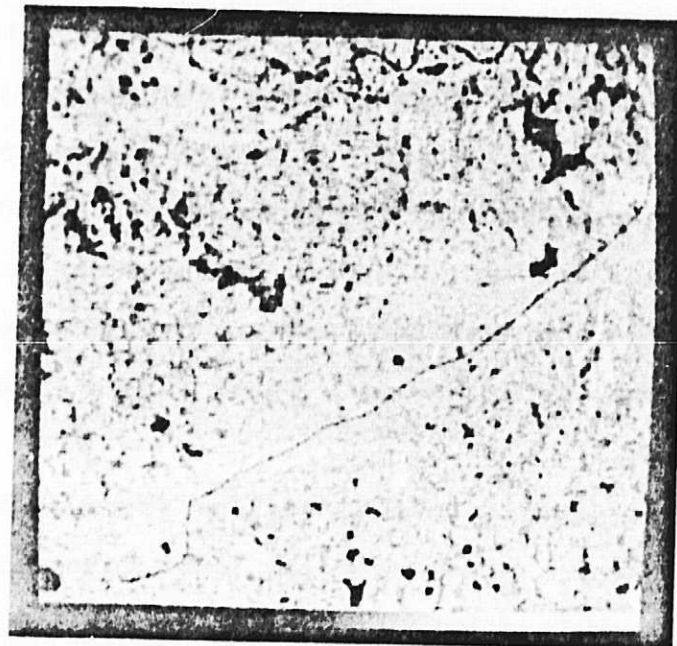
is large ($N \geq 23$). Hence, the variance in P_r within a given portion of the scene is only minimally dependent upon signal fading and is mostly the result of variance in local topographic relief, radar backscatter category, and near-surface soil moisture. In a visual sense, the interaction of relief, category, and moisture yield quite different spatial patterns of P_r on each of the three simulation dates. This is best seen in the 100 m by 100 m radar resolution imagery. Figure 12 shows enlargements of the northwest (upper-left) quadrant of the 100 m by 100 m imagery for each of the three overpass dates. This quadrant encompasses the test site used in previous orbital radar simulations [1, 2, and 6]. These images illustrate the following:

- 1) For nearly uniform soil moisture conditions, the variance in P_r is dominated by local topographic relief and radar backscatter category. This condition is most closely approximated by Julian day 150 in Figure 12b.

- 2) For variable soil moisture conditions, the scene variance in P_r is most closely related to local soil moisture and radar backscatter category which tends to mask variance in P_r related to local topographic effects. This condition is best seen on Julian day 160 (Figure 12c) since an extended period of evapotranspirative losses in soil moisture has enhanced the relative difference in P_r from each radar backscatter category.

The above indicates the potential for achieving certain

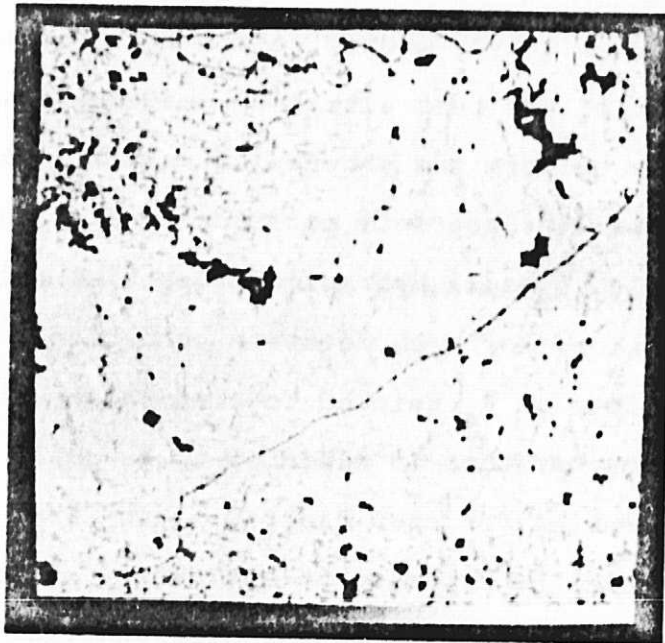
ORIGINAL PAGE IS
OF POOR QUALITY.



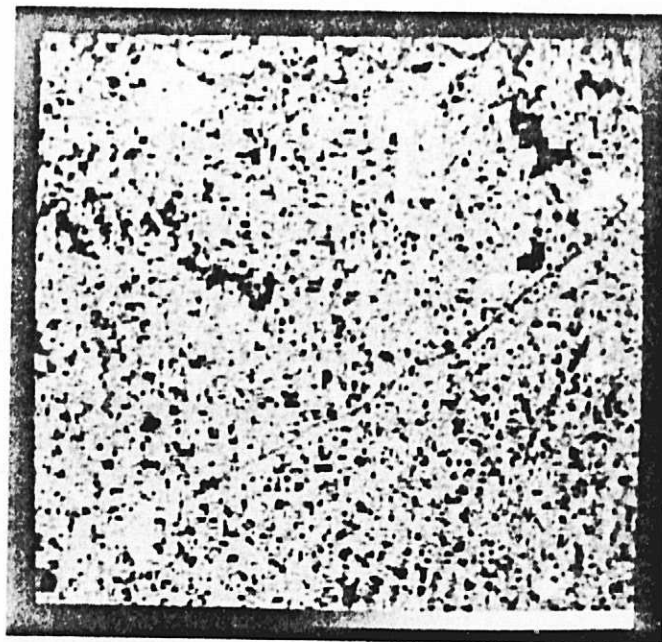
(a) Julian day 141

Figure 12. Enlargements of the northwest corner of the simulated 100 m by 100 m resolution radar imagery on each overpass date.

ORIGINAL PAGE IS
OF POOR QUALITY



(b) Julian day 150



(c) Julian day 160

mapping objectives not rigorously addressed within the confines of this study. First, the potential exists to classify soil type within relatively flat agricultural portions of the test site from imagery acquired shortly after a nearly uniform and saturating rainfall event. In this case, near-surface soil moisture is high and largely controlled by soil hydraulic properties related to soil type. In addition, for high moisture conditions, the relative uncertainty in P_r related to crop-canopy attenuation and canopy backscatter is expected to be small [5]. Secondly, the potential for crop discrimination from orbital radar imagery can be expected to maximize (for this frequency and angle of incidence) when the differential evapotranspirative dry-down of each crop has enhanced the inter-crop variance in P_r . This condition would exist five or more days after a rainfall event.

4.0 SOIL MOISTURE CLASSIFICATION

In order to classify soil moisture using the simulated radar imagery, a generalized soil-moisture algorithm is derived from all experimental data for bare and vegetation-covered soil conditions (excluding woodlands). The classification algorithm relates estimated soil moisture \hat{M}_{fs} to received power P_r as a function of incidence angle θ .

$$\hat{M}_{fs} = [P_r - \alpha(\theta)]/\beta(\theta) \quad (3)$$

where

$$\alpha(\theta) = 9.67 + 0.84\theta - 4.59 \times 10^{-2}\theta^2 + 8.27 \times 10^{-4}\theta^3, \text{ and}$$

$$\beta(\theta) = 0.161 + 9.38 \times 10^{-4}\theta - 4.97 \times 10^{-4}\theta^2 + 1.21 \times 10^{-5}\theta^3.$$

In this case, θ is estimated from the range position of a pixel on the radar image, assuming spherical earth geometry and a constant mean elevation of the test site above sea level. Thus, the classification algorithm is "blind" with respect to true local incidence angle and to the actual backscattering category of any given pixel [6]. Application of this algorithm to the received power images yields maps of estimated soil moisture, an example of which is shown in Figure 13 for a radar resolution of 100 m by 100 m on Julian day 141.

Given the above algorithm, orbital radar imagery can be used to classify soil moisture in two ways. First, the imagery obtained at any given radar resolution on any single overpass date can be passed through the general algorithm (Equation 3) to yield estimates of the absolute soil moisture distribution for that date. The second approach is to make use of the multi-temporal coverage provided by an orbital system to yield estimates of the relative change in soil moisture. The radiometric and geometric stability of the Seasat-A L-band imaging radar has shown that such a procedure is feasible and relatively uncomplicated from the standpoint of image registration [8]. The two approaches are not

ORIGINAL PAGE IS
OF POOR QUALITY

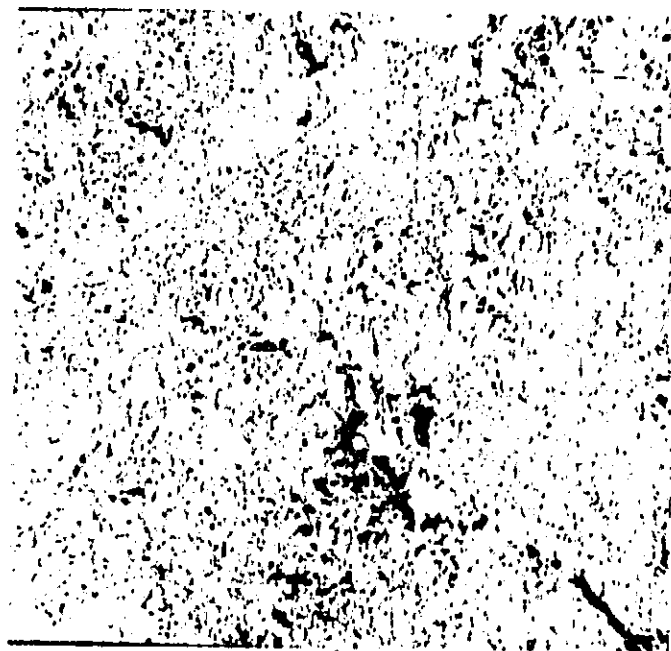


Figure 13. Near-surface soil moisture as estimated for Julian day 141
from simulated radar imagery with a 100 m by 100 m resolution.

mutually exclusive and both will be explored in the ensuing sections with respect to soil moisture classification error as a function of radar resolution and the geographic distributions of local relief and backscatter category.

4.1 Single Date Soil-Moisture Classification Accuracy

The accuracy of soil-moisture classification is examined by evaluating the difference between the true soil moisture M_{fs} and the estimated soil moisture \hat{M}_{fs} . This is accomplished through registration of the two images (such as Figures 6 and 13) and computation of the difference. Due to the geometric distortion inherent in the radar image-forming process, image registration by simple coordinate translation is only accurate to within about ± 1.3 pixels (130 meters), and this registration error is proportional to changes in local elevation across the image swath. Hence, a procedural error is introduced into the comparative process which is not related to true classification error. Also, the magnitude of this procedural error is proportional to the local variance in the "true" soil moisture distributions as shown in Figure 6.

In order to examine the effects of various land-use and field-size distributions, four subregions are identified within the test site and relate to an urban area, mixed cropland, pasture and rangeland, or woodland. Figure 2 shows the spatial locations of these subregions, and their land-use

and field-size distributions are tabulated in Tables 1 and 2, respectively. All subregions contain more than 30% pasture, grass, and rangeland, and are distinctive primarily in terms of the percent area occupied by cultural features (residential, buildings, and roads), water, woodland, and crops. In addition, the rangeland/pasture subregion is characterized by a greater percentage of large fields as compared to the other subregions. Finally, Figure 2 shows that the woodland and the rangeland/pasture subregions are located in areas of relatively large local relief.

An example of soil-moisture classification error is shown in Figure 14 for the 100-m by 100-m resolution radar on Julian day 141. Classification error E_m is defined by

$$E_m = M_{fs} - \hat{M}_{fs} \quad (4)$$

where

M_{fs} = true soil moisture, and

\hat{M}_{fs} = estimated soil moisture.

Figure 14a shows the category classification map for the woodland subregion where wooded areas are black, water is dark gray, cultural features are white, and agricultural land and pasture/rangeland are generally light gray. The difference between actual soil moisture M_{fs} and classified soil moisture \hat{M}_{fs} is mapped in Figure 14b. E_m is linearly represented by graytone and thus, dark and white areas represent overestimation and underestimation of soil moisture, respectively. The large P_c from cultural features



(a) Backscatter category map: woods are black, water bodies are dark gray, cultural features are white, and agricultural areas are light gray.



(b) Soil moisture estimate error E_m : overestimates of soil moisture are dark, underestimates of soil moisture are white, areas with small estimate errors are gray.

Figure 14. Soil moisture classification error E_m on Julian day 141 within the woodland subregion resulting from use of the "blind" classifier on 100 m by 100 m radar imagery.

at A leads to an overestimation of moisture, while the low P_r from woodland at B and water at C yields a low estimate of soil moisture. Median gray tones in Figure 14b relate to small estimate errors. A comparison of Figures 14a and 14b shows moisture-estimate errors to be highly correlated with the spatial location of specific land-use categories, especially cultural features, trees, and water. Image registration errors yield white or black rings around specific features. Hence, the spatial organization of such confusion categories largely determines the moisture classification accuracy of a given radar resolution for a given geographic land-use setting.

The single date soil moisture classification error can be examined as a function of radar resolution, general soil moisture condition (overpass date), and geographic subregion.

The soil moisture classification error E_m resulting from radar resolutions of 100 m by 100 m, 1 km by 1 km, and 3 km by 3 km is shown for the entire 124-km by 108-km test site on each overpass date in Figure 15. For all general soil moisture conditions (overpass dates), the distributions of E_m resulting from classification of the 100-m resolution imagery are more peaked and yet have longer tails than the corresponding distributions of E_m for the coarser resolutions. These long tails are related to the presence of confusion categories such as urban features, woodland, and water. The effects of these confusion categories at the coarser resolutions (1 km by 1 km and 3 km by 3 km) are to

OF POOR QUALITY

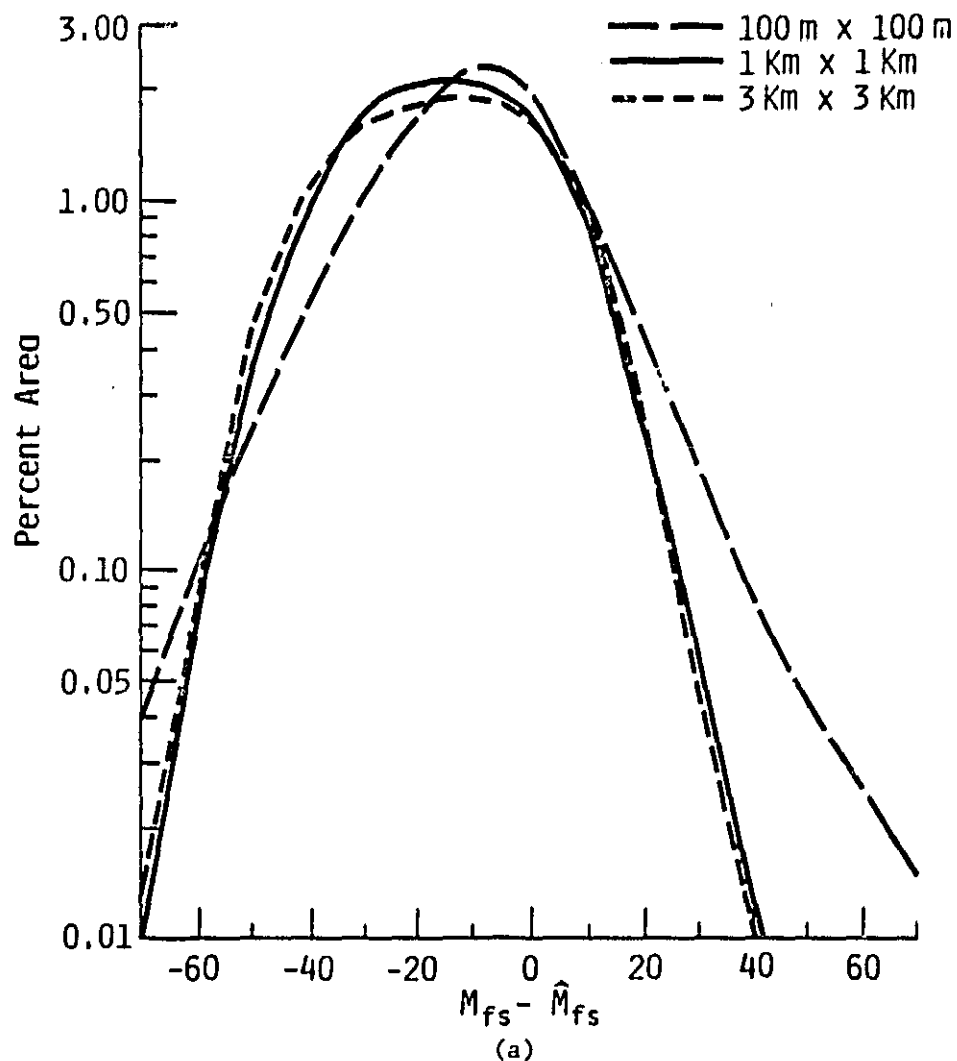
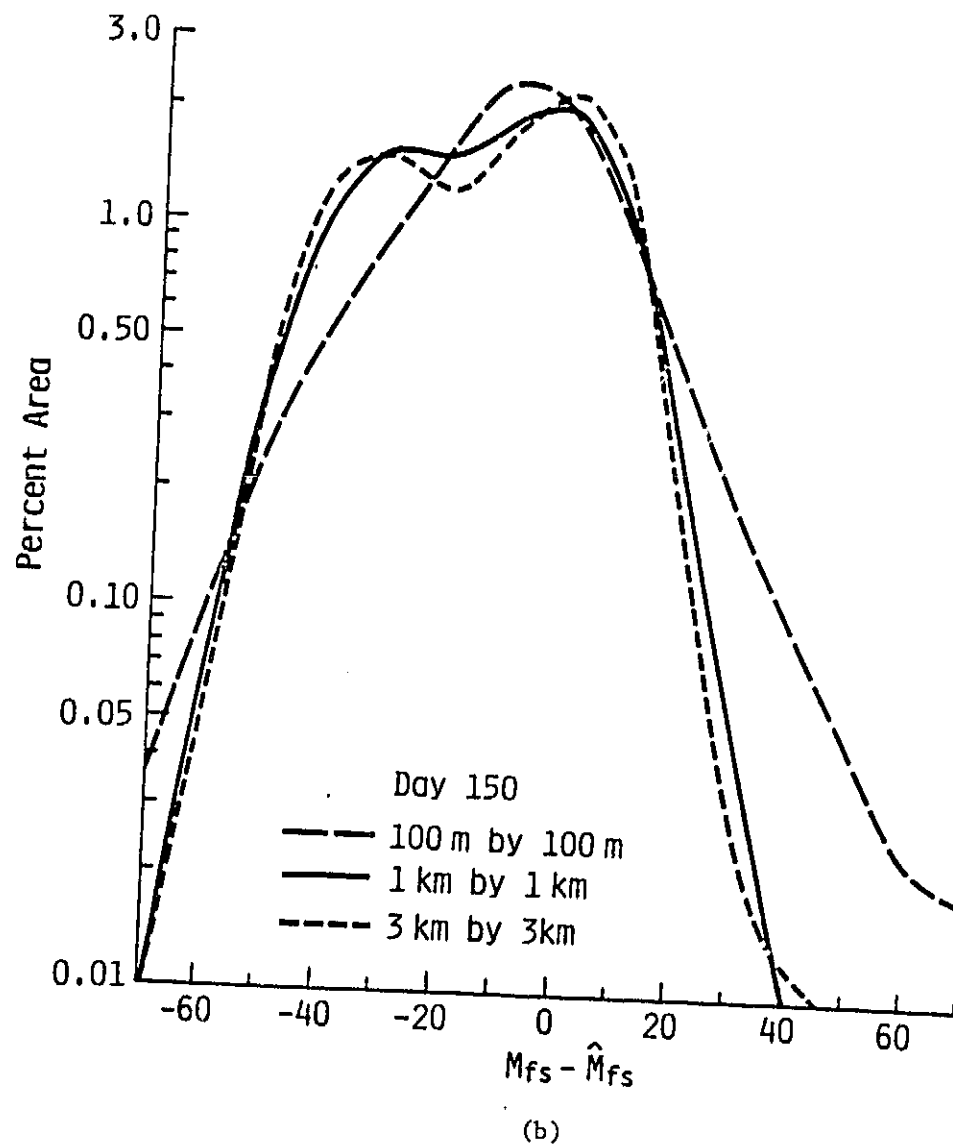
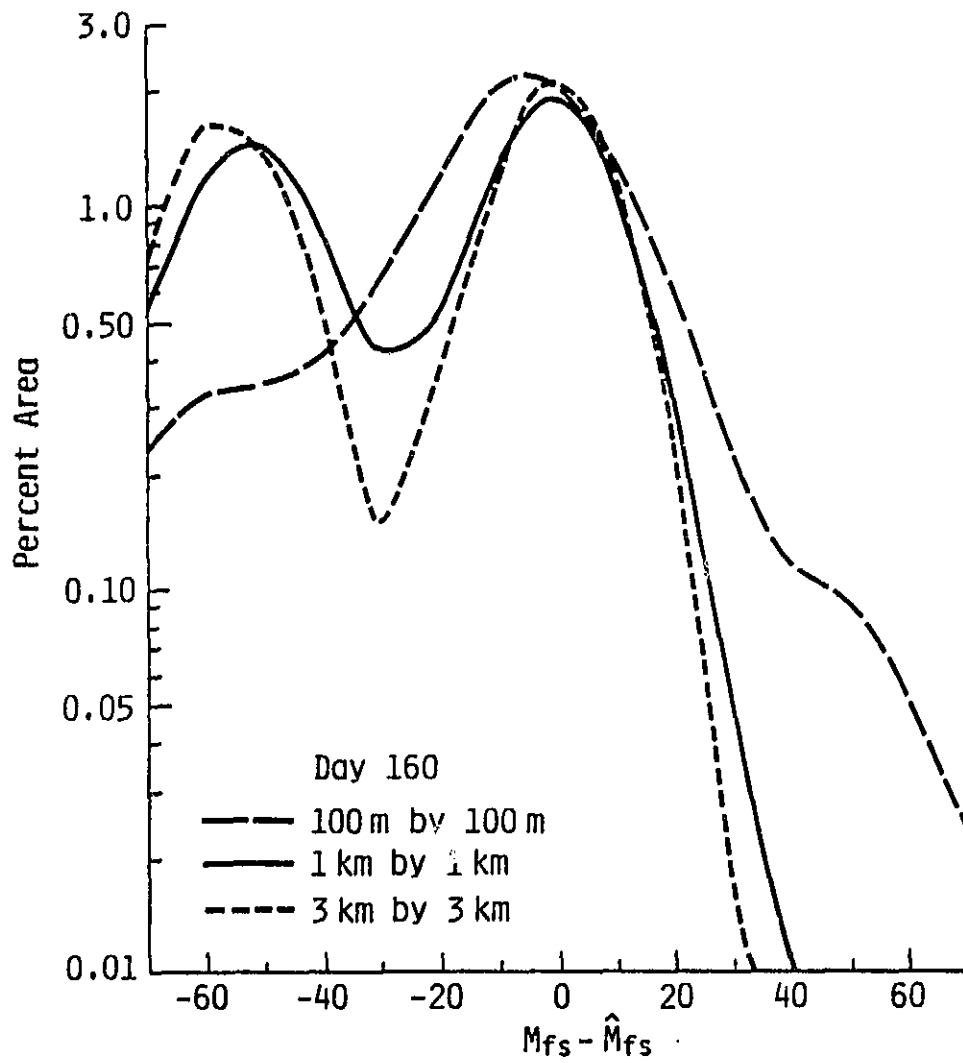


Figure 15. Soil moisture classification error E_m resulting from each radar resolution for all moisture dependent pixels in the test site (excluding woods) on a) Julian day 141, b) Julian day 150, and c) Julian day 160.

ORIGINAL PAGE IS
OF POOR QUALITY



ORIGINAL PAGE IS
OF POOR QUALITY



(c)

broaden the error distribution.

The tendency of the coarser resolutions (1 km by 1 km and 3 km by 3 km) to yield bimodal distributions of E_m in Figure 15 with a secondary peak ranging from -30% to -50% is primarily related to the presence of cultural features which have large scattering cross-sections relative to agricultural and rangeland areas. These overestimates of local soil moisture result from averaging the large P_r from cultural targets over a larger area. Hence, the magnitude of this secondary peak is proportional to both the net area occupied by cultural features and the dispersion of such features within the total scene, and the size of E_m at this peak is proportional to the ratio of P_r cultural to P_r agricultural.

The associated absolute moisture classification accuracies of the three radar resolutions are shown in Figure 16. In general, the 100-m by 100-m resolution is shown to yield the most accurate estimates of soil moisture. For example, use of the "blind" generalized moisture algorithm on Julian day 141 yields \hat{M}_{fs} within +/- 20% of true moisture M_{fs} for 68% of the area using a radar with a 100-m resolution, while only 60% and 58% of the area is classified within this error limit using radar resolutions of 1 km and 3 km, respectively. In Figures 14 and 15, this result is shown to be related to the spatial distribution of land-use confusion categories.

The differences in absolute classification accuracy between the three radar resolutions are also dependent upon

ORIGINAL DATA
OF POOR QUALITY

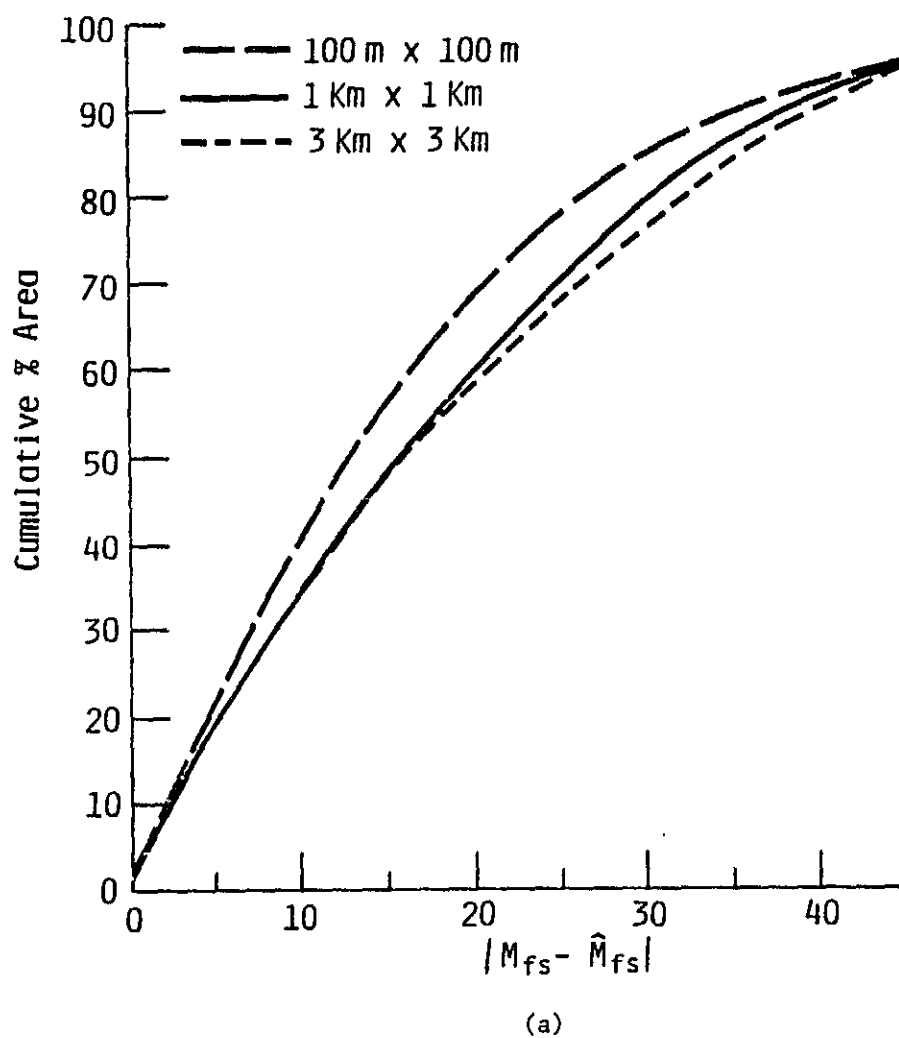
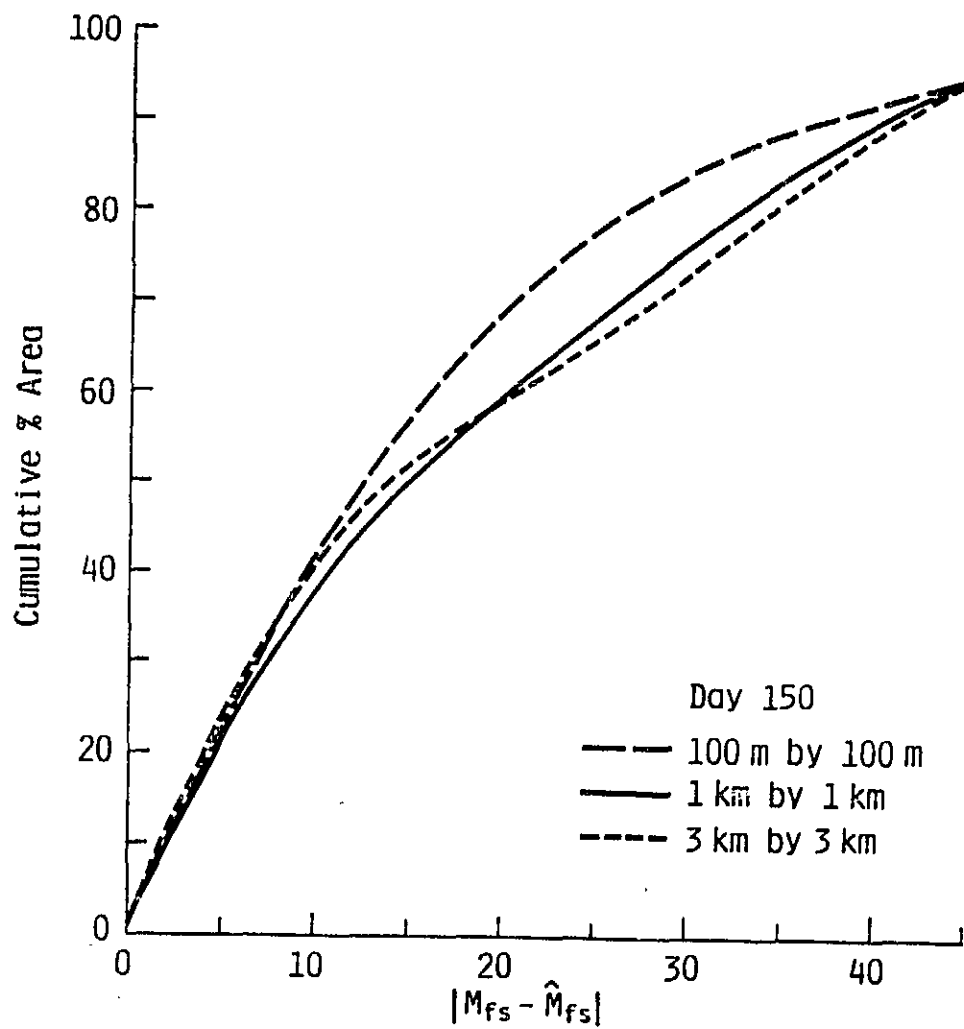


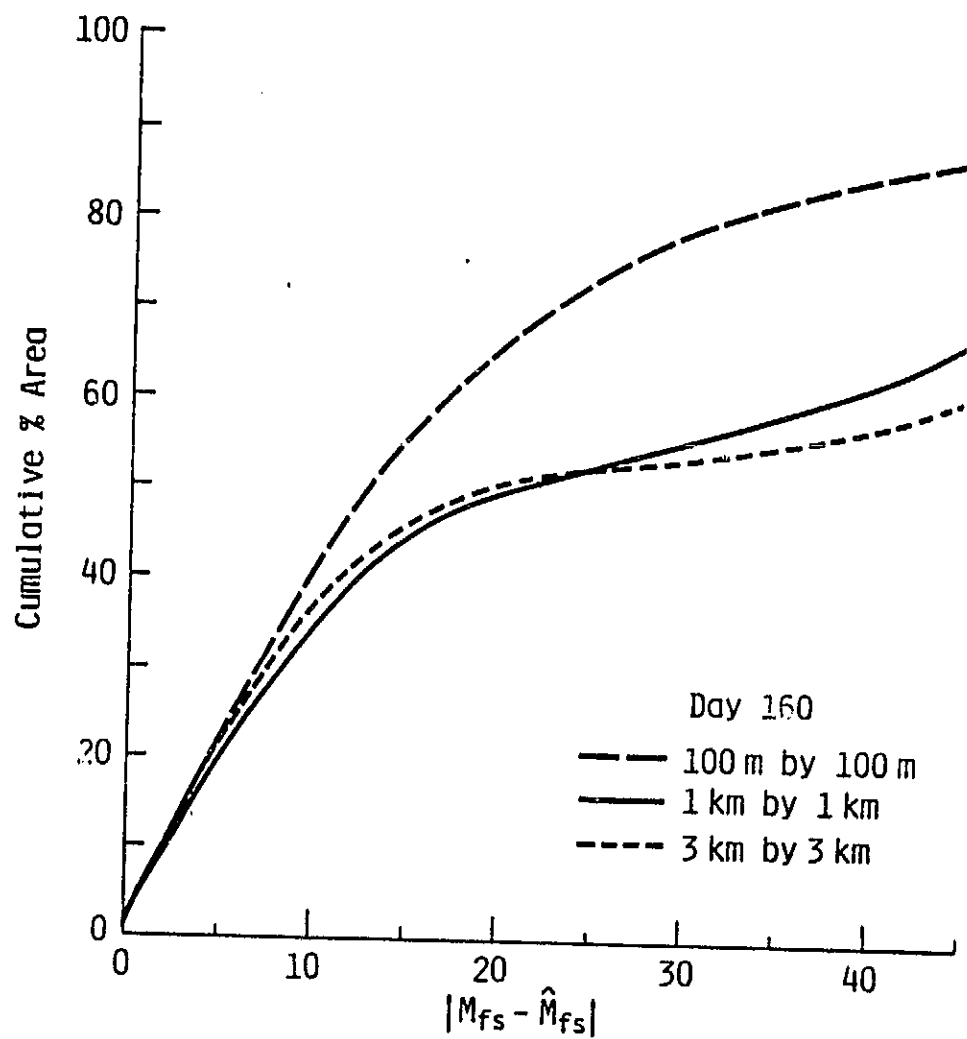
Figure 16. Cumulative percent area of all moisture dependent pixels in the test site (excluding woods) as a function of absolute moisture classification error for each radar resolution.

ORIGINAL: 11/11/10
OF POOR QUALITY



(b)

ORIGINAL SOURCE
OF POOR QUALITY



(c)

general soil moisture condition. This effect is seen by comparing the results achieved for different overpass dates in Figure 16a, b, and c for overpasses on Julian days 141, 150, and 160, respectively. The classification accuracy of the coarse resolution sensors (1 km by 1 km and 3 km by 3 km) is seen in Figure 16c to be significantly reduced relative to the classification accuracy achieved with the 100 m resolution radar. The local variance in true soil moisture M_{fs} and local received power P_r are seen to be greatest on Julian day 160 in Figures 6 and 12, respectively. As previously stated, this is largely the result of the differential evapotranspirative dry-down rates of the various crop canopies constituting the scene. Thus, the within-scene variance in soil moisture M_{fs} is highly correlated with the crop distribution given in Table 1 which is dispersed in aggregates given by the field size distribution (Table 2). Hence, at radar resolutions coarser than field size a serious degradation in moisture classification accuracy can be expected for imagery acquired during periods of protracted evapotranspirative loss.

The effects on moisture classification error of varying the local distribution of land-use confusion categories are demonstrated by comparing the error distributions for the four land-use subregions. The error distributions for the urban, pasture/rangeland, cropland, and woodland subregions are compared in Figure 17, based upon the 100-m resolution radar imagery for Julian day 141. When the error

ORIGINAL PAGE IS
OF POOR QUALITY

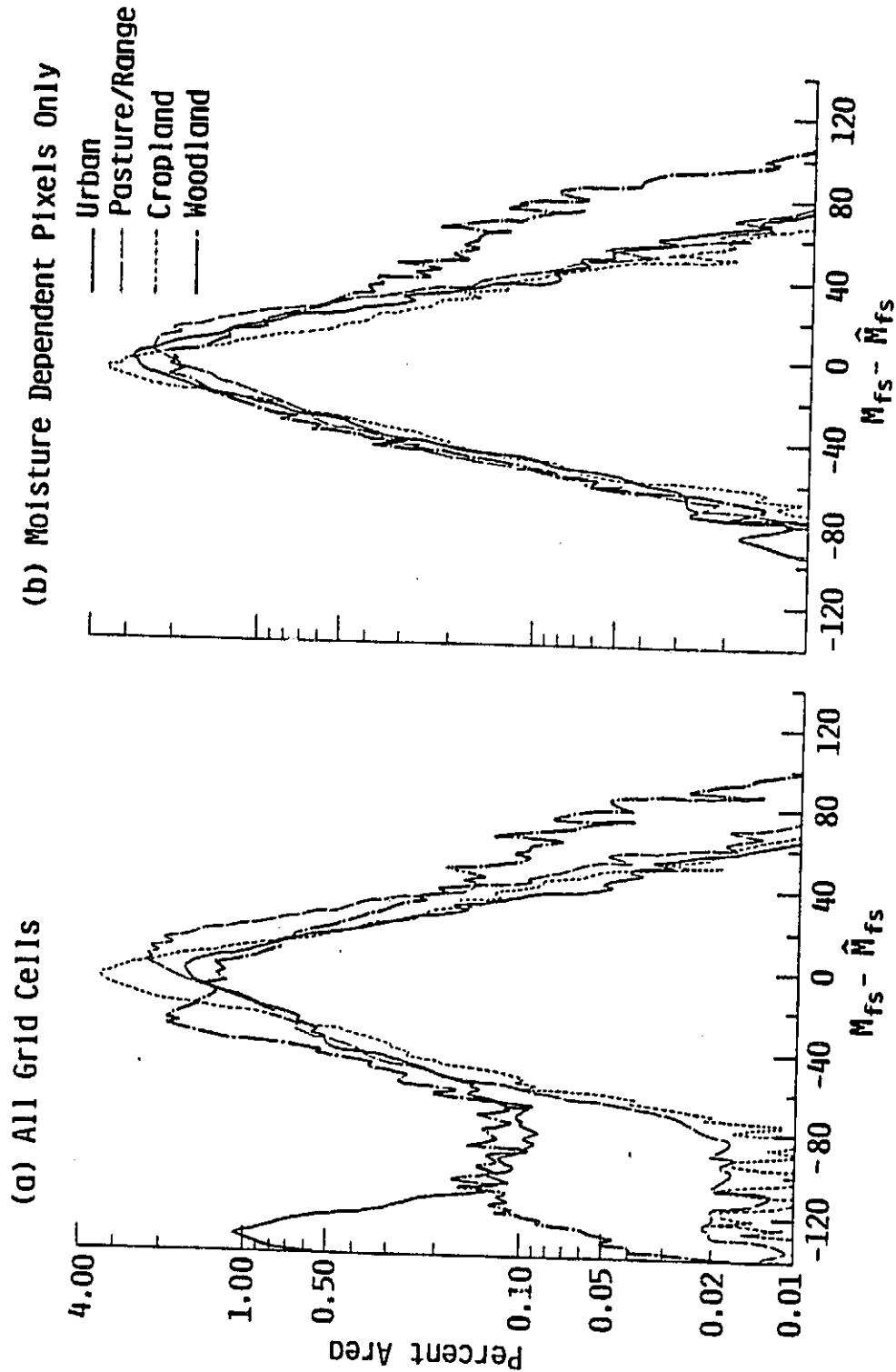


Figure 17. Distribution of the difference between actual and classified soil moisture for the subregions of the test site as computed from 100-m resolution radar imagery for Julian day 141.

distribution is plotted for all 100-m by 100-m grid cells within each region (Figure 17a), large overestimates of moisture, primarily in the urban and woodland subregions, are related to the presence of cultural features such as buildings and roads and also related to the presence of water bodies since for these categories soil moisture is undefined and any moisture estimate for these categories is therefore an overestimate. In a similar fashion, large underestimates of M_{fs} , best exemplified by the woodland subregion, are largely related to the presence of deciduous trees, which are assumed to fully attenuate backscattering from the soil at 4.75 GHz.

The exclusion of nonagricultural categories (cultural features, water, and woodland) from the grid-cell comparisons of \hat{M}_{fs} to M_{fs} yields highly peaked distributions centered around ≈ 0 error as shown for each subregion in Figure 17b. The woodland still exhibits a larger area where soil moisture is underestimated than the other subregions and this is largely the result of locally saturated to flooded soil moisture conditions. The radar backscatter model treats fully saturated soil as a near specular surface similar to a water body, and hence P_r is low at off nadir incidence angles. As a consequence, soil moisture M_{fs} is generally underestimated. Similar results are obtained for the other two overpass dates.

The absolute classification accuracy for Julian day 141 within each of the four land-use subregions is shown in

Figures 18a and 18b from simulated radar resolutions of 100 m by 100 m and 1 km by 1 km respectively. As expected from the above and from the distributions of land-use categories and field-size given in Tables 1 and 2, Figure 18a shows that the greatest classification accuracy is achieved for the cropland subregion and the poorest for the woodland subregion. Based upon land-use and field-size distributions alone, one would expect a greater absolute classification accuracy for the pasture/rangeland subregion than for the urban subregion in Figure 18a; however, the greater local topographic variation present within the pasture/rangeland subregion (Figure 1) leads to moisture classification errors related to the variance in local slope, which is unknown to the "blind" classification algorithm. This same effect also suppresses the absolute classification accuracy for the woodland subregion which is also "hilly" in nature.

For a 1-km by 1-km resolution radar, the combined effects of the spatial distribution of land-use categories (the relative mix of categories and their respective size distributions) and topographic relief upon absolute classification accuracy yield the results shown in Figure 18b. For areas where local topographic relief varies over spatial dimensions of hundreds of meters, the 1-km by 1-km radar resolution will tend to average local slope-related variance in P_r , and thus yield absolute classification accuracies greater than those achieved by a finer resolution sensor (such as 100 m by 100 m). This appears to be the case

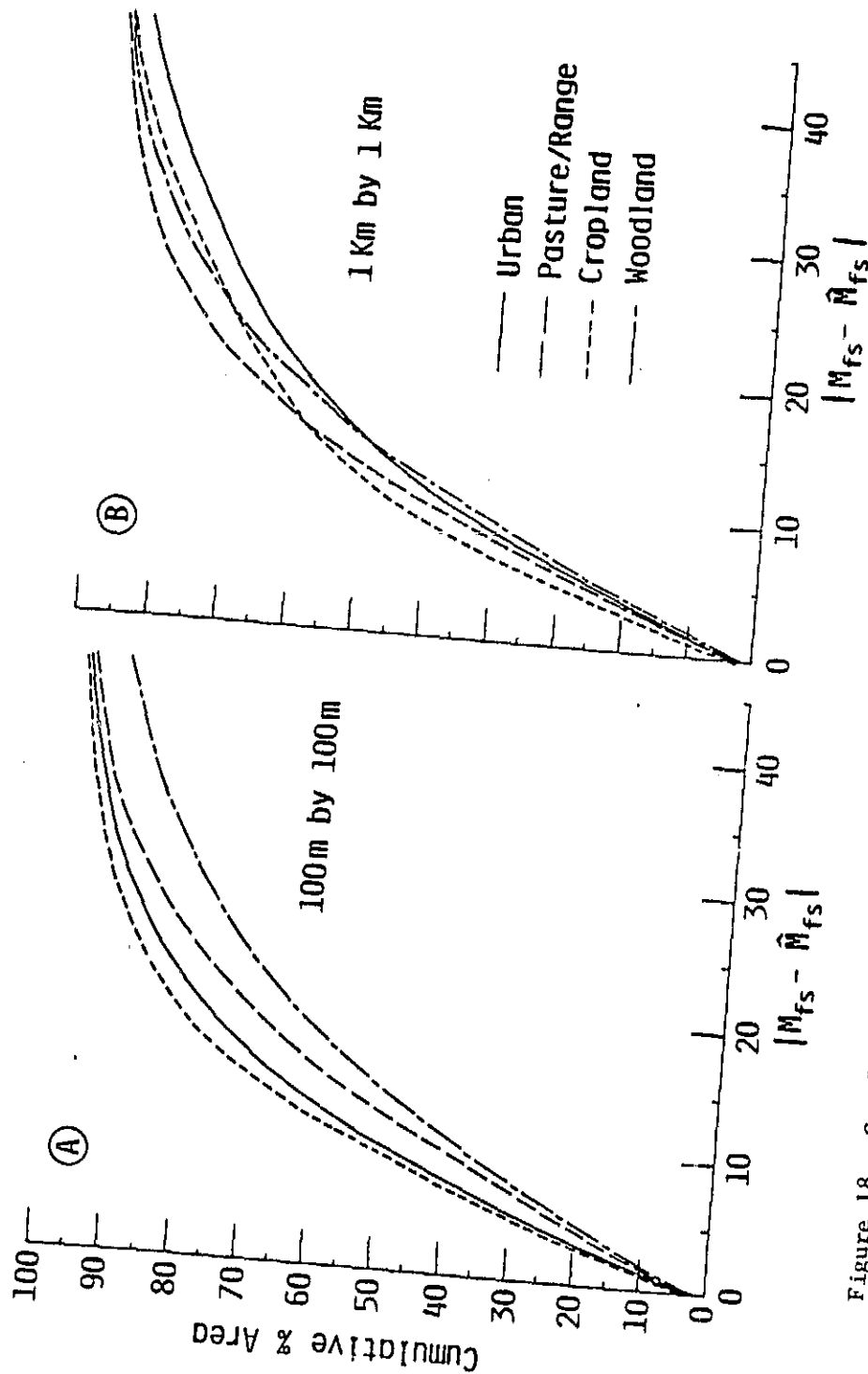


Figure 18. Cumulative percent area correctly classified as to soil moisture versus maximum classification error (only moisture-dependent grid cells are compared).

for the pasture/rangeland and woodland subregions of the test site. For example, at an absolute accuracy level of $\pm 20\%$ of field capacity, Table 5 shows that the percent area correctly classified within this limit from the 100-m resolution radar is 71.3% and 64.1% for the pasture/rangeland and woodland subregions, respectively; and the percent area correctly classified from the 1-km resolution radar increases to 79.4% and 73.3% for the two subregions, respectively.

Conversely, for areas characterized by a large number of dispersed cultural targets (with generally large P_T), the use of a coarse-resolution radar, such as 1 km by 1 km, is shown to degrade absolute moisture classification accuracy relative to that achievable by a 100-m by 100-m resolution sensor; this effect is demonstrated by the urban and cropland subregions. For example, in Figure 18 the effect of dispersed cultural features and field size distribution leads to a decrease in percent of the urban subregion which is correctly classified to within $\pm 20\%$ of field capacity from 77.9% (100-m radar resolution) to 70.1% (1-km radar resolution). In a similar fashion, the percent area correctly classified to within $\pm 20\%$ of field capacity for the cropland subregion decreases from 82.0% to 75.6% for the 100-m and 1-km radar resolutions, respectively.

The above results for Julian day 141 are not independent of general soil moisture condition and the spatial variability of soil moisture. The absolute soil moisture classification accuracies for each of the four subregions are

TABLE 5. Percent of Moisture Variant Area Correctly
Classified to Within ± 20 of True Soil Moisture
($|E_m| \leq 20\%$)

| Julian Day | 141 | | | 150 | | | 160 | | |
|-------------------|-------|------|------|-------|------|------|-------|------|------|
| Radar Resolution | 100 m | 1 km | 3 km | 100 m | 1 km | 3 km | 100 m | 1 km | 3 km |
| Subregions | | | | | | | | | |
| Cropland | 82.0 | 75.6 | 74.3 | 87.5 | 91.0 | 91.8 | 77.4 | 73.9 | 75.6 |
| Urban | 77.9 | 70.1 | 65.0 | 75.3 | 83.6 | 86.9 | 76.2 | 63.7 | 58.5 |
| Rangeland/Pasture | 71.3 | 79.4 | 80.4 | 72.5 | 80.4 | 82.3 | 77.0 | 74.6 | 77.4 |
| Woodland | 64.1 | 73.3 | 72.7 | 72.6 | 83.6 | 86.0 | 68.3 | 68.5 | 68.4 |

shown for Julian days 150 and 160 in Figures 19 and 20, respectively. In addition, the percent area correctly classified to within $\pm 20\%$ of field capacity are also given for each date and radar resolution in Table 5.

For the generally wet soil conditions prevalent on Julian day 150, comparison of the results shown in Figure 19 and Table 5 as a function of orbital radar resolution indicates that estimate accuracy increases with the additional spatial averaging provided by the coarse resolution radars for all subregions. This is explained by the distribution of soil moisture for this date which is primarily governed by the antecedent rainfall pattern. Since a large quantity of rain fell within most of the test site just prior to the simulated orbital overpass, the local properties of slope, soil texture, and crop canopy condition have not had sufficient time to exert a large influence and vary local soil moisture distributions. As a result, the added spatial averaging provided by the coarser radar resolutions acts to increase classification accuracy by averaging small spatial scale noise effects related to local relief and variance in local radar backscattering category. This is true even for the urban scene; since at very high soil moisture conditions, the P_r from wet agricultural fields approaches that from the cultural features.

Within the four subregions, the dependence of soil moisture classification accuracy upon radar resolution is shown in Figure 20 and Table 5 for the generally dry and

CRITERIA FOR OF POOR QUALITY

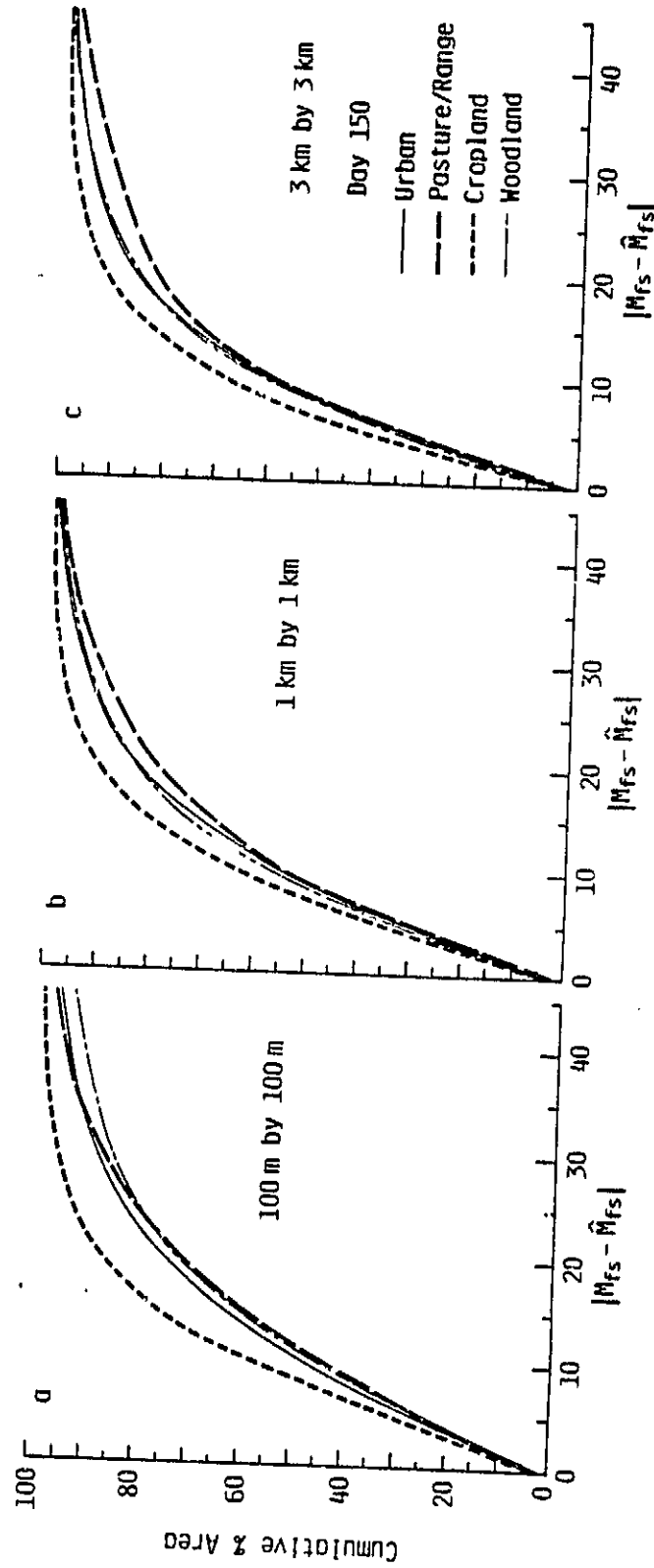


Figure 19. Cumulative percent area of all moisture dependent pixels in each subregion as a function of absolute moisture classification error on Julian day 150.

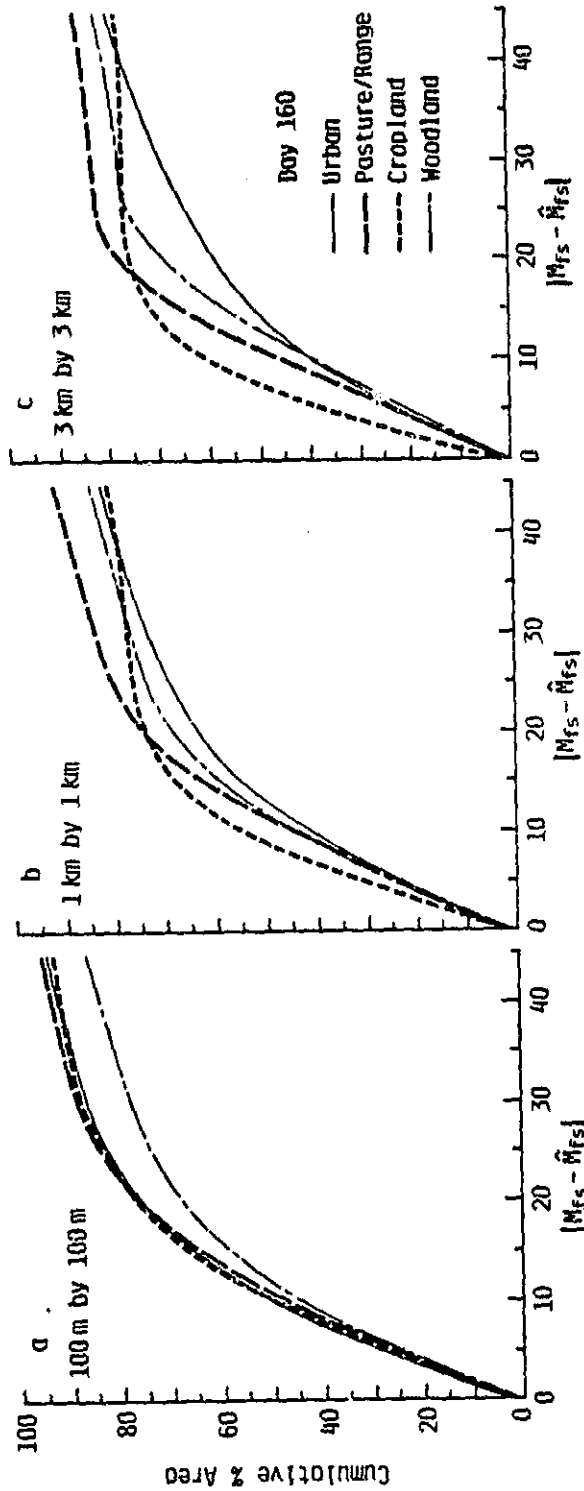


Figure 20. Cumulative percent area of all moisture dependent pixels in each subregion as a function of absolute moisture classification error on Julian day 160.

spatially variable soil moisture conditions prevalent on Julian day 160. Classification accuracy is shown to be independent of radar resolution for absolute estimate error $|M_{fs} - \hat{M}_{fs}|$ less than 20% of field capacity for the cropland, rangeland/pasture, and woodland subregions. However, as radar resolution is degraded the areal percentage of the cropland and woodland subregions with large absolute estimate errors, $|M_{fs} - \hat{M}_{fs}| \geq 30$, does increase significantly. This is attributed to the large local variance in true soil moisture M_{fs} within these subregions on Julian day 160. The most extreme example of local variance in M_{fs} is given by the urban subregion which exhibits a pronounced decrease in classification accuracy as radar resolution is degraded.

4.2 Multidate Change Detection of Soil Moisture

The preceeding section shows that absolute moisture classification accuracy from a single date orbital radar observation is limited by the presence of scene confusion factors within the imagery and their size and spatial dispersion relative to the radar resolution. Within the present discussion, scene confusion factors are defined both as the presence of scene elements for which soil moisture is unidentified such as buildings, roads, water bodies, etc. and also the occurrence of variability in $P_r(\theta)$ from scene elements possessing equivalent soil moisture. The latter results from natural variability in topographic slope, crop canopy type and stage of growth, row direction, and surface

roughness.

In single date sensing and classification of soil moisture, the confusion effects of cultural features and water bodies can be minimized (but not eliminated) by spatial filtering. Two approaches are feasible. First a simple intensity slice of the received power $P_r(\theta)$ could be used to roughly define water (dark) and point targets such as buildings (bright) within the image, the remainder of the image could then be subjected to the "blind" moisture classification algorithm. However, this approach cannot be expected to yield consistent results since for very dry soil moisture conditions many agricultural targets can appear similar to water (Figure 8a) or the water may be roughened by wind. In addition, for very wet soil conditions, many agricultural targets will be characterized by P_r near nadir similar to that from the point targets (Figure 8c). A second, more satisfactory approach would be to incorporate a priori knowledge of the spatial distribution of such features and filter them from moisture classification. This, of course, assumes the availability of a Level I land-use classification which could be scaled and rectified to the orbital radar imagery.

In a similar fashion, the moisture classification error related to natural variability within the agricultural portions of the scene could be reduced if the radar data can be registered to topographic and crop distribution data. This would assume a mechanism for crop discrimination and

classification. In this case, each pixel element in the radar image could be classified as to soil moisture using an algorithm tailored to be crop specific. Obviously, this approach is not currently feasible.

However, since most of the confusion factors are spatially fixed and relatively invariant over short periods of time (excepting wind conditions), their effects on moisture classification accuracy can be minimized more economically by the multi-temporal change detection approach. In this technique, the radar imagery acquired at two dates are coregistered and their ratio yields a map of scene change. This process has been shown to be relatively simple to implement with L-band orbital imagery obtained by Seasat-A [8]. For a constant imaging geometry on the two dates (angle of incidence and azimuth view angle), the backscattered power received from cultural targets should remain approximately constant and that received from water bodies should remain nearly constant depending upon local wind conditions. Hence, these features should display little or no change in the multirate ratio images. On the other hand, all scene elements subject to change in backscatter category (such as planting, harvest, and tillage of agricultural fields) and/or subject to change in near-surface soil moisture status will yield a corresponding change in the multirate ratio images. If the time separation in multi-date observation is short relative to changes in crop development, then changes apparent in the ratio images will reflect relative moisture

change and/or field status change related to tillage operations. Since surface slope is constant over the time interval, row direction is time constant in the absence of tillage, and surface roughness decays only slowly with time, the impact of these confusion factors upon the ratio of multirate received power should be negligible.

The soil moisture distributions and the radar imagery simulated for Julian days 150 and 160 (wet and dry, respectively) are used to evaluate the utility of change detection for monitoring relative change in near-surface soil moisture. The change in actual soil moisture ΔM_{fs} between the two dates is shown in Figure 21. The graytone values in the image are linearly scaled to the difference function given as:

$$\Delta M_{fs} = M_{fs}(150) - M_{fs}(160) \quad (5)$$

where the value in parentheses refers to Julian date. In producing Figure 21, a constant value of 128 (of 255 maximum) was added to ΔM_{fs} , hence medium gray values such as those for the Kansas City area denote no change in soil moisture, bright areas denote considerable drying over the 10 day period, and dark areas denote an increase in near-surface (0-5 cm) soil moisture. In general, Figure 21 shows that drying conditions are prevalent over most of the test site except for scattered areas located primarily in the western portion (left side) due to rainfall (see Figure 5).

Multirate registration of the radar imagery simulated at

ORIGINAL PAGE IS
OF POOR QUALITY

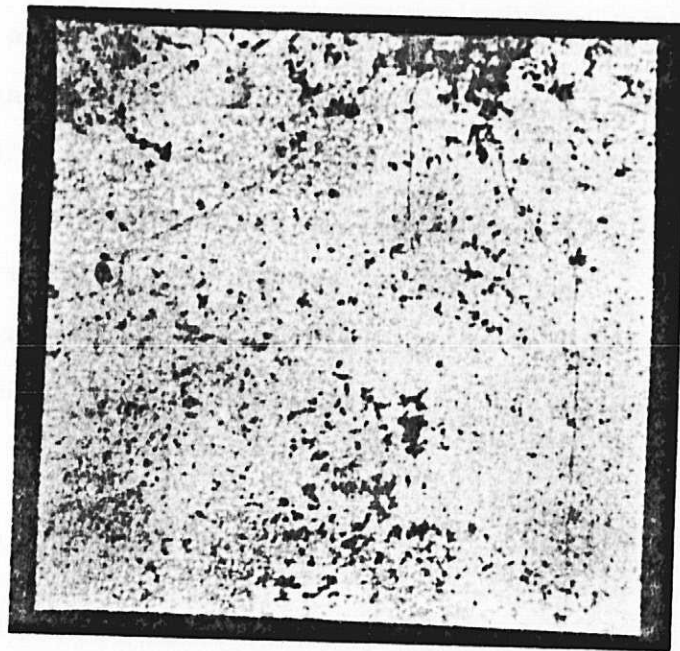
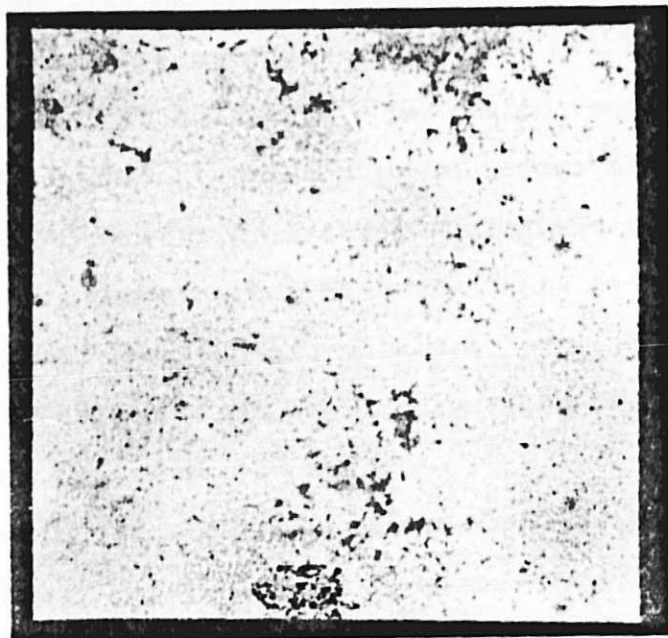


Figure 21. Change in actual soil moisture between Julian days 150 and 160; medium gray indicates no change in soil moisture, bright areas indicate drying over the period, and black areas indicate an increase in soil moisture.

each of the three resolutions yields difference images which are scaled to $\hat{\Delta M}_{fs}$ via the blind classification algorithm (Equation 2). Image presentations of predicted change in soil moisture $\hat{\Delta M}_{fs}$ are shown for each radar resolution in Figure 22. In general, the direction (wetting or drying) and the magnitude of the true change in soil moisture observed in Figure 21 are faithfully reproduced for all radar resolutions. A notable exception to this can be observed at the bottom center of each image in Figure 22. The black area denotes a predicted increase in soil moisture which is not observed in Figure 21. This discrepancy is the consequence of saturated to partially flooded soil conditions on Julian day 150 and moist conditions on Julian day 160 for this area. Hence, actual soil moisture has decreased while that predicted shows an increase since under flooded conditions the radar backscatter models generally yield low values of P_r comparable to that from a water body.

The area distributions of actual moisture change ΔM_{fs} and that predicted from the radar imagery $\hat{\Delta M}_{fs}$ are plotted in Figure 23. The sharp spike in the ΔM_{fs} distribution at zero change is related to cultural features and water bodies. In general, it is apparent that the distribution of predicted moisture change $\hat{\Delta M}_{fs}$ as derived from the 100 m resolution radar most closely approximates the actual ΔM_{fs} distribution. The spatial averaging of the coarser radar resolutions causes them to be less sensitive to relatively large local change in ΔM_{fs} and thus the magnitude and extent of such changes tends

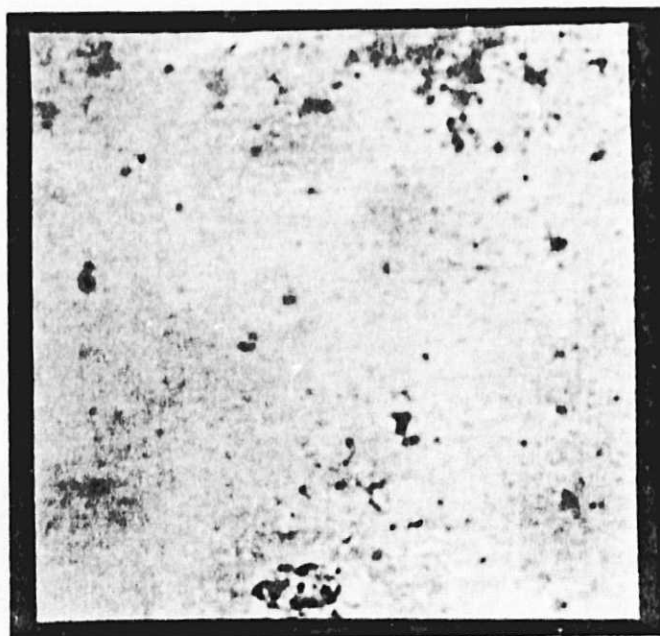
ORIGINAL PAGE IS
OF POOR QUALITY



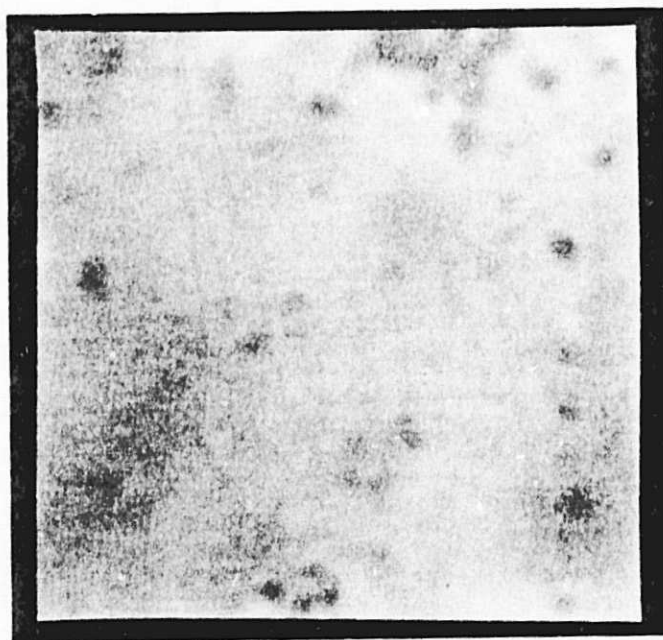
(a) 100 m by 100 m radar resolution.

Figure 22. Predicted change in soil moisture between Julian days 150 and 160 based on multitime radar imagery.

ORIGINAL PAGE IS
OF POOR QUALITY



(b) 1 km by 1 km radar resolution.



(c) 3 km by 3 km radar resolution.

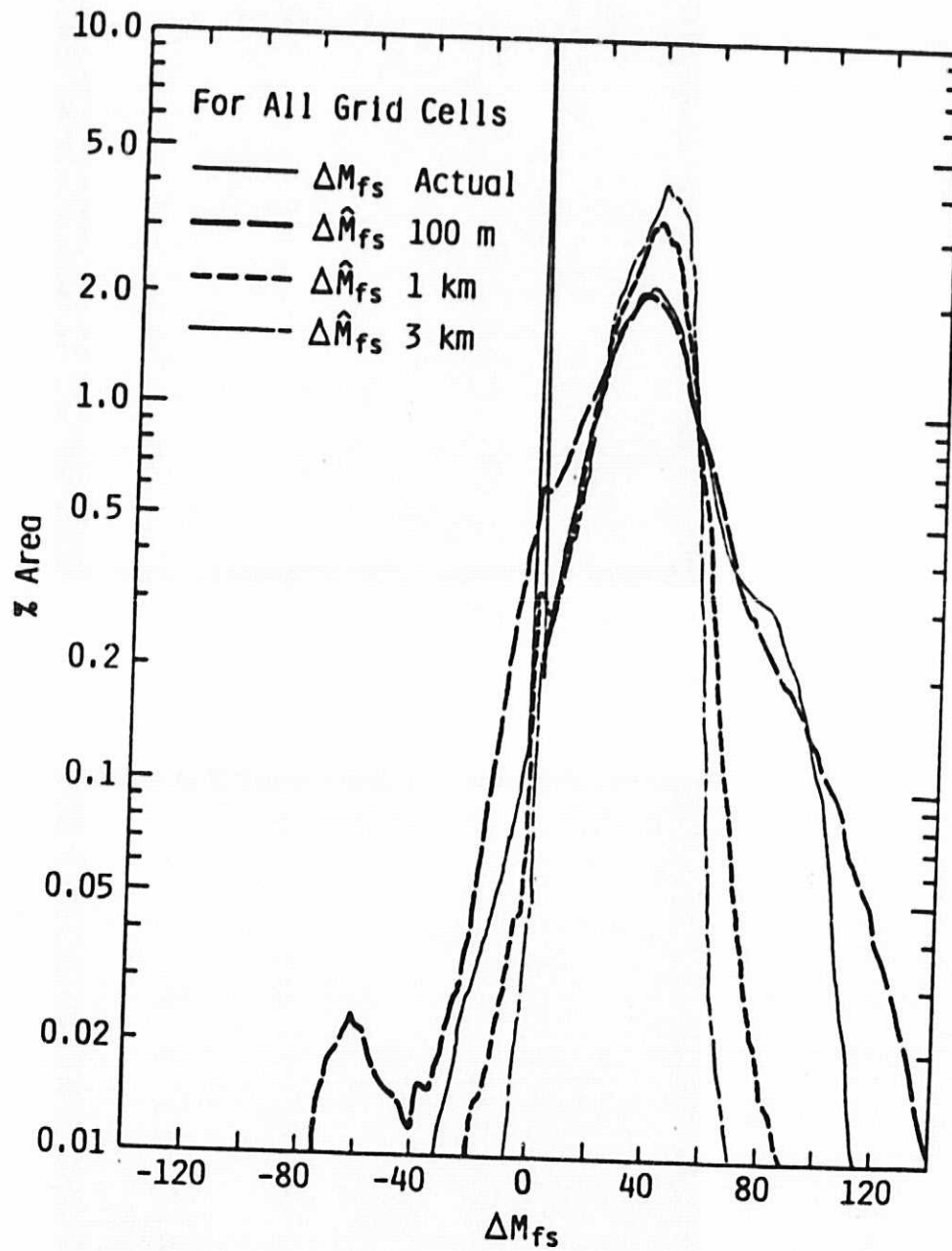


Figure 23. Distributions of actual ΔM_{fs} and predicted $\Delta \hat{M}_{fs}$ change in soil moisture.

to be underpredicted.

The actual and predicted change in soil moisture can be compared on a grid cell basis by registration of the images in Figures 21 and 22. This procedure is, of course, subject to the registration errors discussed earlier for single date moisture classification due to changes in image geometry and position. For each pixel, the error in predicting relative moisture change can be defined as:

$$E_{\Delta M} = \Delta M_{fs} - \hat{\Delta M}_{fs} \quad (6)$$

The spatial distribution of $E_{\Delta M}$ is shown for each radar resolution in Figure 24. The brightest area on the scale bar denotes regions where the absolute magnitude of $E_{\Delta M}$ is within $\pm 10\%$ of ΔM_{fs} and as graytone decreases the areas correspond to $|E_{\Delta M}|$ limits of $\pm 20\%$, $\pm 30\%$, and $\pm 40\%$ respectively as shown on the scale bar. For the 100 m resolution radar, 90% of the area is correctly classified to within $\pm 20\%$ of ΔM_{fs} and greater than 90% of the area to within $\pm 30\%$ of ΔM_{fs} . In addition, most of the residual error is randomly distributed except for some classification error of large magnitude which is related to offsets in mechanical image registration as exemplified by linear features such as roads. For degraded radar resolutions of 1 km and 3 km, the magnitude of classification errors increase and are spatially associated with edges between backscatter categories.

The comparative error in moisture-change estimates $E_{\Delta M}$

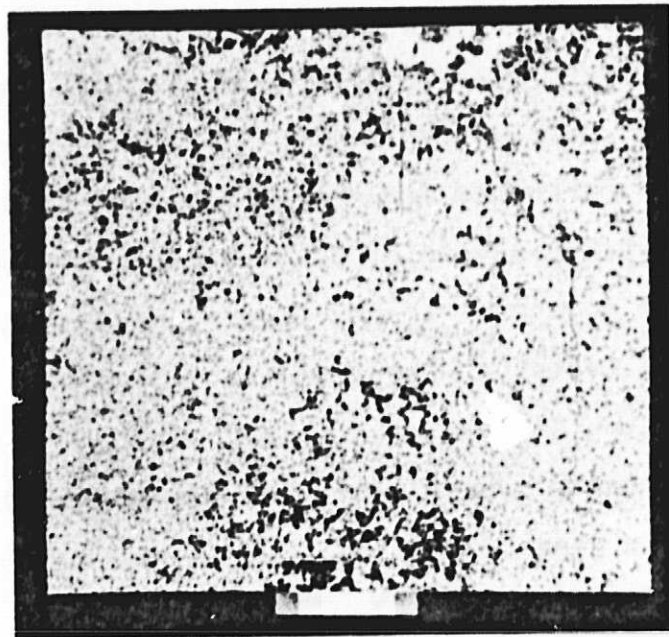
ORIGINAL PAGE IS
OF POOR QUALITY



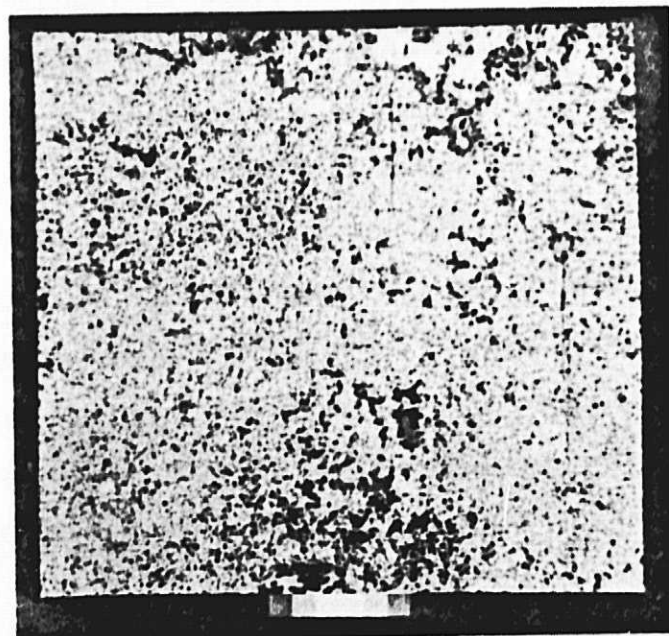
(a) 100 m by 100 m radar resolution.

Figure 24. Spatial distribution of difference between actual change in soil moisture and that predicted from multistate radar observation.

ORIGINAL PAGE IS
OF POOR QUALITY



(b) 1 km by 1 km radar resolution.



(c) 3 km by 3 km radar resolution.

for the three radar resolutions is shown in Figure 25 for all 1.34 million grid cell comparisons within the test site. The corresponding percent of total area (124 km by 108 km) with absolute classification error less than a given magnitude is plotted in Figures 26a. Obviously, the 100 m resolution radar exhibits superior classification accuracy. However, if only the moisture variant pixels are compared (excludes cultural features, water bodies, and woodland) the distinction between resolutions shown in Figure 26b is not statistically significant; 78% and 89% of the area is correctly classified to within $\pm 20\%$ and $\pm 30\%$ of ΔM_{fs} , respectively.

The effect of geographic subregion on the above results is shown in Figure 27. For the 100 m resolution radar, the change detection analysis results in superior classification accuracies for areas characterized by gentle topographic relief (cropland and urban subregions). For the coarser radar resolutions shown in Figure 27b and c, two effects are noted. First the influence of edges related to variance in the magnitude of ΔM_{fs} between adjacent backscatter categories causes classification accuracy for all subregions to decrease relative to that for the rangeland/pasture subregion which is characterized by large field sizes. Secondly, the absolute classification accuracy decreases as a function of resolution for all subregions except rangeland/pasture. The large relative field size within the rangeland/pasture subregion and the large percent area occupied by range and pasture

ORIGINAL PAGE IS
OF POOR QUALITY

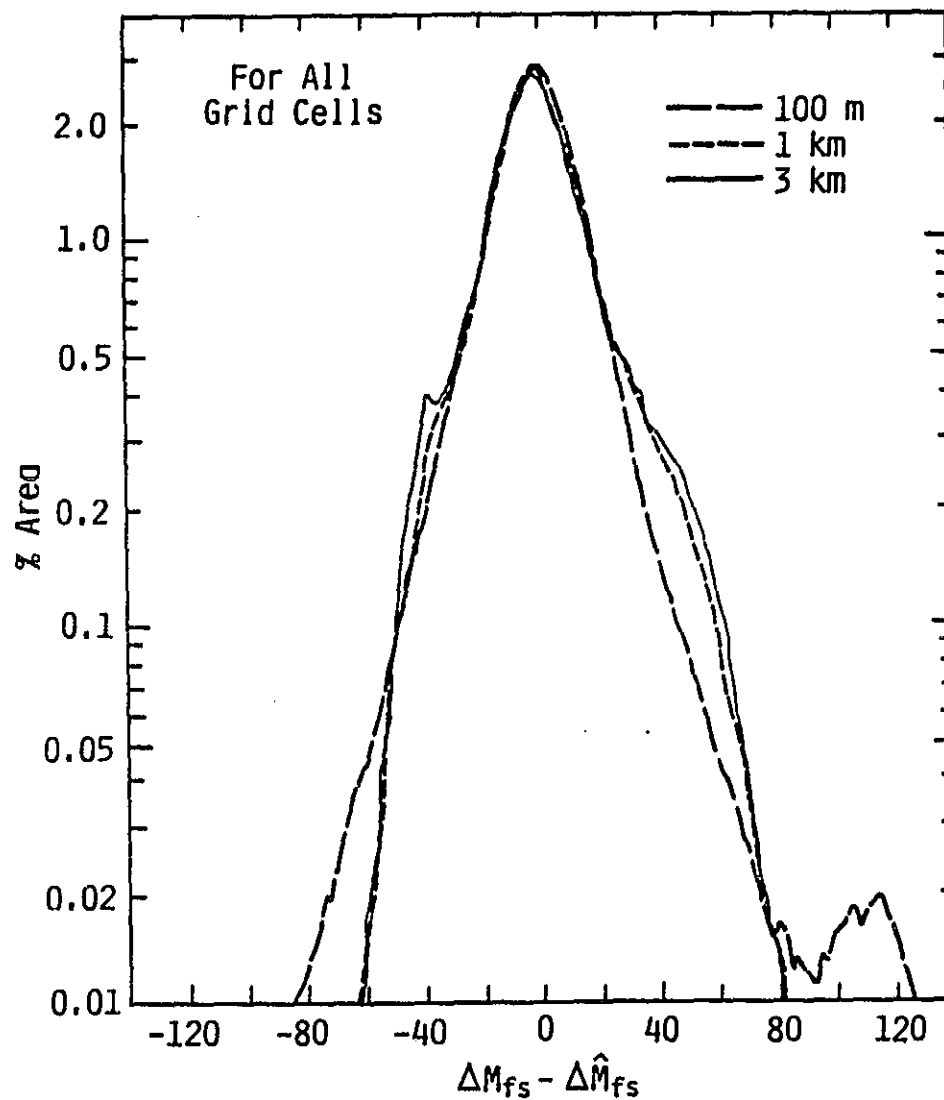
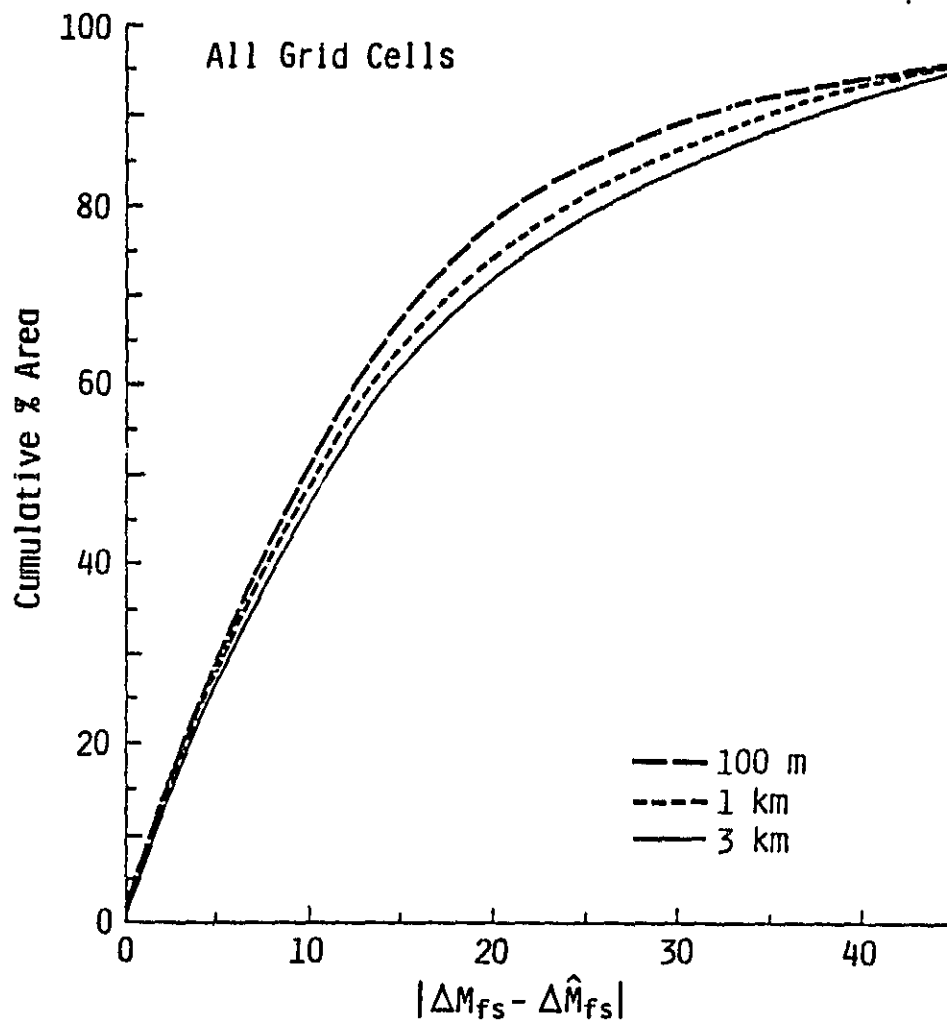


Figure 25. Magnitude of error in estimates of relative soil moisture change as a function of test site area.

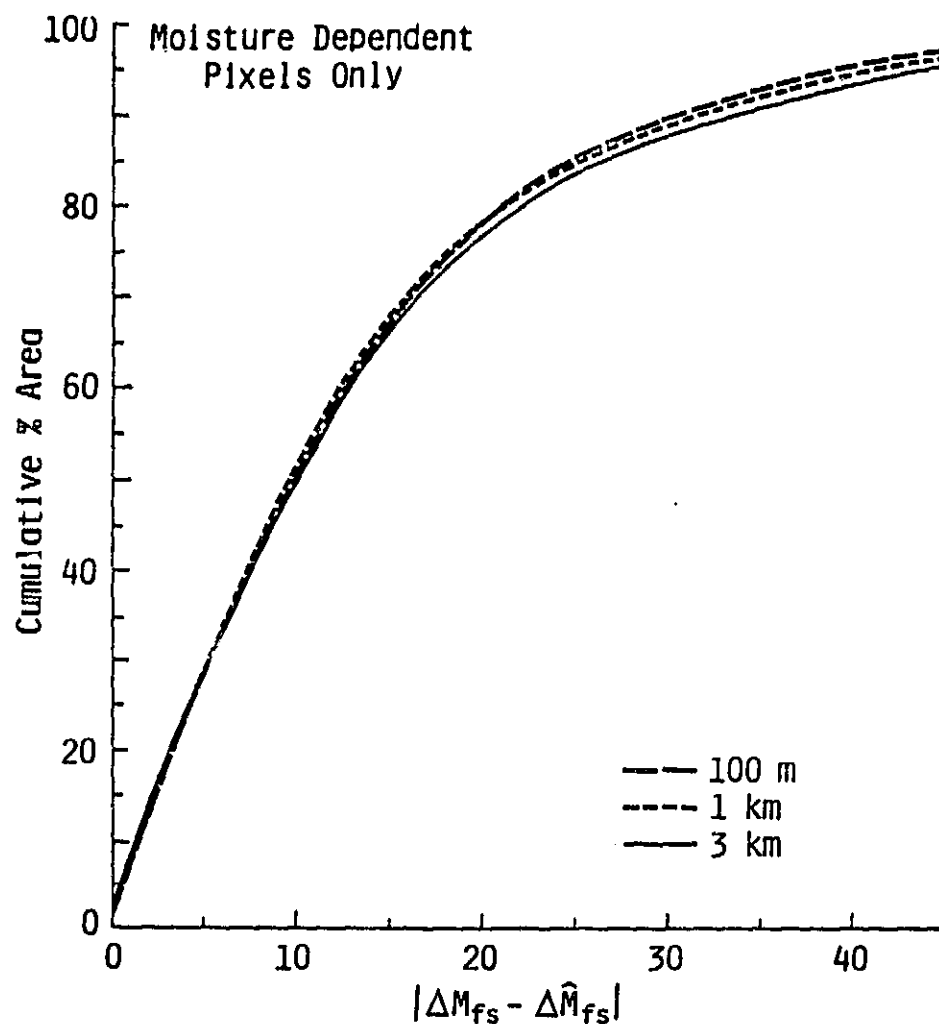
ORIGINAL LATEST ED
OF POOR QUALITY



(a) Full test site, 1.34 million grid cell comparisons.

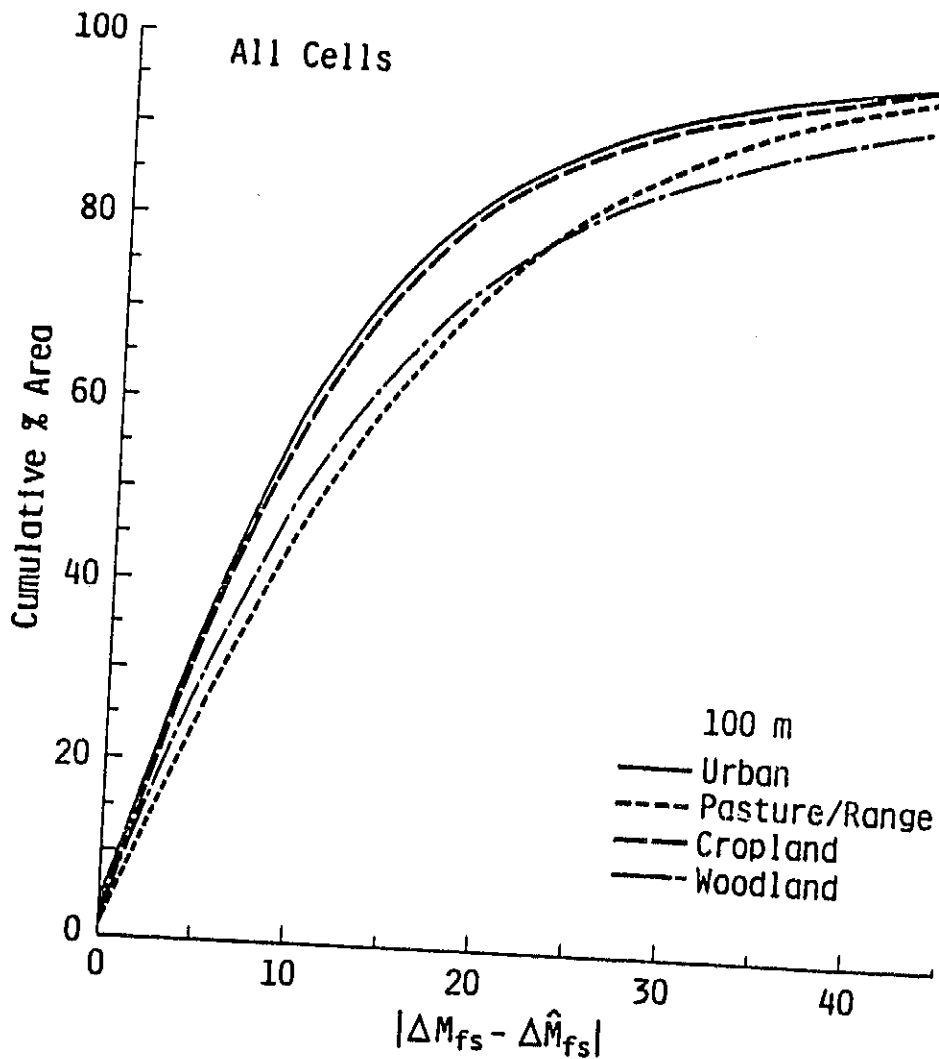
Figure 26. Percent of test site area wherein relative change in soil moisture is correctly classified versus magnitude of classification error.

CLIMATE DATA
OF POOR QUALITY



(b) Moisture dependent categories only, 1.20 million grid cell comparisons, excludes cultural features, water bodies, and woods.

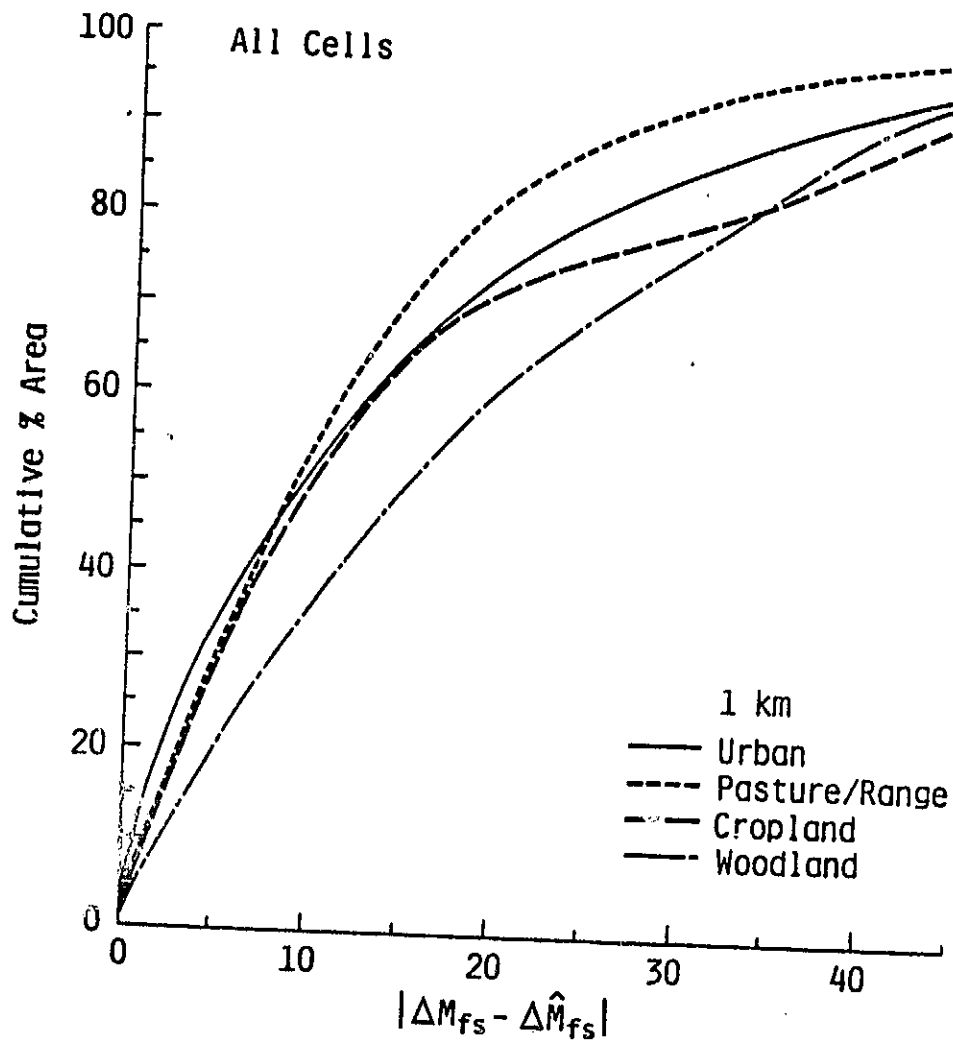
ORIGINAL PAGE IS
OF POOR QUALITY



(a) 100 m by 100 m radar resolution

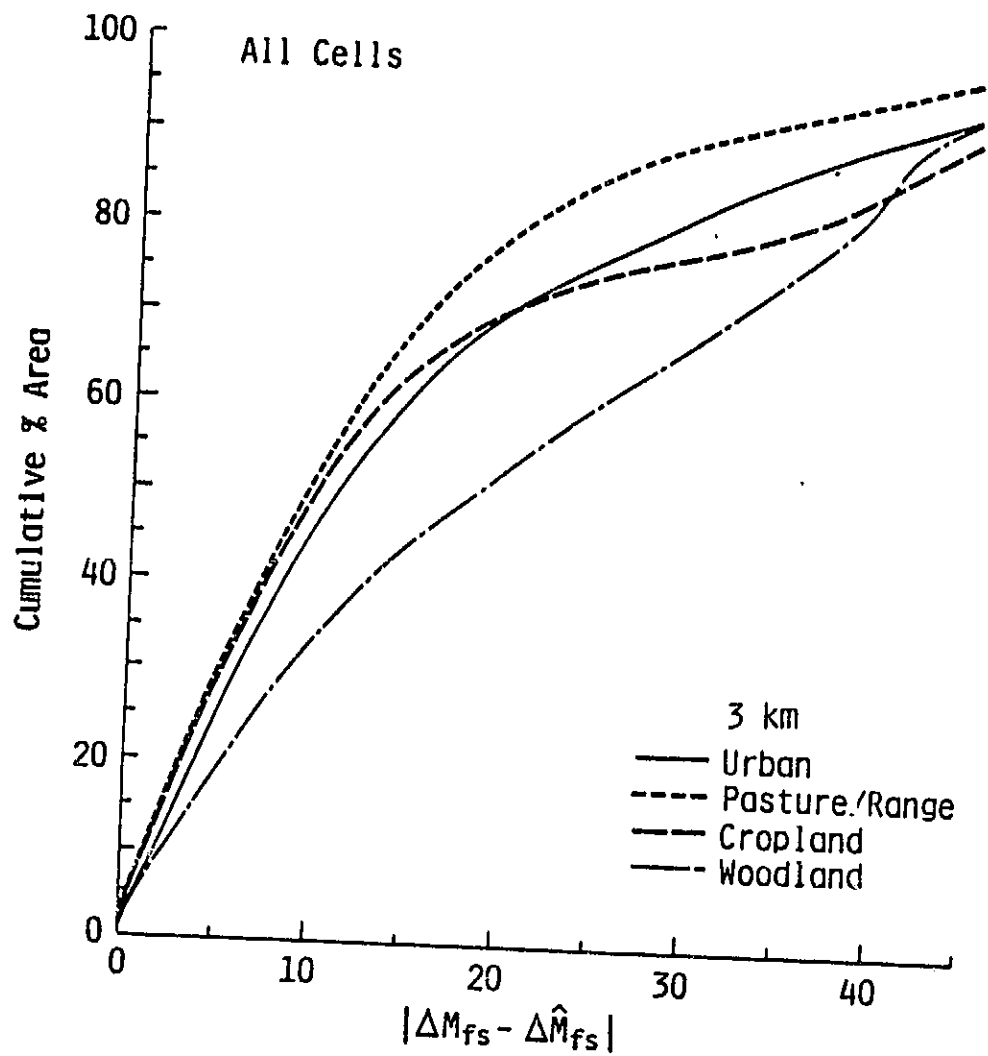
Figure 27. Percent of each subregion wherein relative change in soil moisture is correctly classified versus magnitude of classification error.

ORIGINAL PAGE IS
OF POOR QUALITY



(b) 1 km by 1 km radar resolution

ORIGINAL PAGE IS
OF POOR QUALITY



(c) 3 km by 3 km radar resolution

(61.5%) is largely responsible for the increase in classification accuracy using 1 km by 1 km radar data relative to that obtained using 100 m by 100 m radar data.

Representative values of classification accuracy within each subregion for an error magnitude of $\pm 20\%$ of ΔM_{fs} are shown in Table 6. These values show that 73% to 83% of the area within any subregion can be correctly classified as to within $\pm 20\%$ of actual soil moisture change for 100 m by 100 m resolution radar imagery. In addition, these values are generally superior to those obtained for single date moisture classification shown in Table 5.

5.0 CONCLUSIONS

This simulation study reconfirms prior results that relatively high single-date moisture-classification accuracies can be achieved from orbital radar operating at 4.75 GHz with HH polarization and at incidence angles of 7° to 17° relative to nadir. Furthermore, this study shows that classification accuracy is optimized for radar resolutions smaller than the expected field-size distribution of extended targets; a nominal sensor resolution on the order of 100 m by 100 m is found to yield the most robust classification results for the majority of tested conditions. In addition, prior results have been extended to show that expected moisture-classification accuracy for a given sensor resolution is not independent of general soil moisture

TABLE 6. Percent Area Correctly Classified to Within +/- 20%
of the True Change in Soil Moisture ΔM_{fs} from
Julian Day 150 to Julian Day 160

| Subregions | All Pixels | | | Moisture Dep. Pixels | | |
|-------------------|------------|-------|------|----------------------|------|------|
| | 100 m | 1 km | 3 km | 100 km | 1 km | 3 km |
| Cropland | 82.4 | 71.4 | 70.8 | 83.3 | 74.0 | 73.6 |
| Urban | 83.4 | 73.9 | 70.5 | 80.4 | 69.8 | 64.2 |
| Rangeland/Pasture | 73.7 | 81.77 | 79.1 | 74.1 | 84.8 | 82.3 |
| Woodland | 74.7 | 60.7 | 52.6 | 72.8 | 73.5 | 73.5 |
| Full Scene | 78.3 | 74.6 | 72.0 | 78.3 | 78.3 | 76.8 |

condition or of the geographical mix of land-use, field-size distribution, and local topography. Finally, the use of multi-date radar imagery to estimate relative change in near-surface soil moisture status is shown to substantially reduce classification errors related to the presence of cultural features and water bodies, the presence of variable crop-canopy covers, and local variability in topographic relief.

Based upon this study, a reasonable approach for the purposes of soil-moisture sensing would be to obtain the data at a sensor resolution on the order of 100 m (with a large number of independent looks) and then degrade the resolution where necessary by post-detection processing to average the moisture classification errors associated with local slope in regions of variable topographic relief. In addition, multi-temporal change-detection analyses could also minimize classification errors controlled by topographic relief as well as those errors that are related to intra- and inter-crop variance in radar backscattering [8].

6.0 ACKNOWLEDGMENTS

This research was supported by the National Aeronautics and Space Administration, Johnson Space Flight Center, Houston, Texas, Grant NCC 9-6.

REFERENCES

- [1] Ulaby, F. T., M. C. Dobson, J. Stiles, R. K. Moore, and J. Holtzman, 1982, "A Simulation Study of Soil Moisture Estimation by a Space SAR," Photo. Eng. Rem. Sens., Vol. 48, No. 4, pp. 645-660.
- [2] Dobson, M. C., F. T. Ulaby, and S. Moezzi, 1982, "Assessment of Radar Resolution Requirements for Soil Moisture Estimation from Simulated Satellite Imagery," RSL Technical Report 551-2, University of Kansas Center for Research, Inc., Lawrence, Kansas.
- [3] Anderson, J. R., et al., 1976, "A Land Use and Land Cover Classification System for Use with Remote Sensor Data," Geol. Surv. Prof. Paper 964, U.S. Government Printing Office, Washington, D.C.
- [4] Hodges, T., 1981, "U.S. Crop Calendars in Support of the Earlier Warning Project," LEMSCO-14674, Lockheed Eng. and Management Services Co., Inc.
- [5] Ulaby, F. T., M. C. Dobson, and D. R. Brunfeldt, 1983, "Improvement of Moisture Estimation Accuracy of Vegetation-Covered Soil by Combined Active/Passive Microwave Remote Sensing," IEEE Trans. Geosc. and Rem. Sens., accepted for publication 1983.
- [6] Ulaby, F. T., M. C. Dobson, J. Stiles, R. K. Moore, and J. Holtzman, 1981, "Evaluation of the Soil Moisture Prediction Accuracy of a Space Radar Using Simulation Techniques," RSL Technical Report 429-1, University of Kansas Center for Research, Inc., Lawrence, Kansas.
- [7] Holtzman, J. C., V. S. Frost, J. L. Abbott, and V. H. Kaupp, 1978, "Radar Image Simulation," IEEE Trans. Geo. Elect., Vol. GE-16, No. 5, pp. 296-303.
- [8] Brisco, B., F. T. Ulaby, and M. C. Dobson, 1983, "Spaceborne SAR Data for Land-Cover Classification and Change Detection," Digest of the 3rd IEEE Intl. Geoscience and Remote Sensing Symp., San Francisco, CA, August 31 - September 2.
- [9] Kansas State Board of Agriculture, 62nd Annual Report and Farm Facts, Topeka, Kansas, 1979.
- [10] Missouri Farm Facts, Missouri Crop and Livestock Reporting Service, Columbia, Missouri, April 1982.
- [11] Peck, A. J., R. J. Luxmoore, and J. L. Stolzy, 1977, "Effects of Spatial Variability of Soil Hydraulic Properties in Water Budget Modeling," Water Resources

Research, Vol. 13, No. 2, pp. 348-354.

- [12] Peak, A. J., R. McQuivey, T. Keefer, E. R. Johnson, and J. Erekson, 1981, "Review of Hydrologic Models for Evaluating Use of Remote Sensing Capabilities," NASA CR 166674, Hydrex Corp., Fairfax, Virginia.
- [13] Hildreth, W. W., 1981, "Comparison of the Characteristics of Soil Water Profile Models," NASA - 15700, Lockheed Eng. and Management Services Co., Inc.
- [14] Jackson, R. D., 1972, "On the Calculation of Hydraulic Conductivity," Soil Sci. Soc. Amer. Proc. Vol. 36, pp. 380-382.
- [15] Armstrong, B. L., 1978, "Derivation of Initial Soil Moisture Accounting Parameters from Soil Properties for the National Weather Service River Forecast System," NOA Technical Memorandum NWS HYDRO 37, National Weather Service.
- [16] Eagleman, J. R., 1971, "An Experimentally Derived Model for Actual Evapotranspiration," Agr. Met., Vol. 8, pp. 385-394.
- [17] Clapp, R. B., and G. M. Hornberger, 1978, "Empirical Equations for Some Soil Hydraulic Properties," Water Res., Vol. 14, No. 4, pp. 601-605.
- [18] Doorenbos, J., and W. O. Pruitt, 1977, "Guidelines for Predicting Crop Water Requirements," FAO Irrigation and Drainage Paper 24, United Nations Food and Agriculture Organization.
- [19] United States Department of Agriculture, 1970, "Irrigation Water Requirements," Technical Release 21, USDA/Soil Conservation Service.
- [20] Hershfield, D. M., 1961, "Rainfall Frequency Atlas of the U.S.," Hydrologic Service Division, Soil Conservation Service, U.S. Department of Agriculture, Washington, D.C.
- [21] Dunin, F. X., 1976, "Its Simulation for Field Conditions," Chapter 8 in J. C. Rodda (ed.): Facts of Hydrology, pp. 199-227, Wiley, London.
- [22] Komp, E. E., V. S. Prost, and J. C. Holtzman, 1983, "Reference Manual for the Radar Image Simulator," RSL Technical Report 581-2, University of Kansas Center for Research, Inc., Lawrence, Kansas.

APPENDIX A

DYNAMIC SOIL WATER ACCOUNTING MODEL

The purpose of a soil water-budget model within the context of realistic radar image simulation is to generate a distribution of near-surface (0-5 cm) soil moisture conditions at the spatial scale of the static terrain data base (100 m x 100 m) which responds to both static conditions (soil type, cover type, and surface slope) and dynamic conditions (crop stage, rain, and potential evaporation) on a time scale relevant to both the dynamics of the process and the orbital mechanics of an imaging satellite (daily basis). While many excellent water-budget models are available for various applications in agronomy and hydrology [11 to 15], no single model meets all the above criteria. Indeed, most such models require more detailed information on soil profile characteristics and weather conditions than is readily available for the simulation area. In addition, most models are designed to operate at a spatial scale much less than field size and over time increments significantly less than one day, or conversely, they are most appropriately applied to very coarse integration times on the order of weeks for a simple set of input parameters and at a macroscopic level much larger than field size.

Because of the large size of the data base (approximately 1,339,000 grid cells), it is necessary to tailor a model that emphasizes the surface horizon and requires a minimum of information as to soil profile and

detailed local weather conditions, and yet is still sensitive to daily variation in soil moisture. A schematic of the final process model is shown in Figure A.1; it consists largely of the following components:

- storm model,
- surface runoff model,
- crop development submodel,
- evapotranspiration model, and
- and interlayer redistribution model.

When given dynamic inputs of crop type, crop stage of development, rainfall, and potential evaporation, the model acts upon the static terrain model to yield daily projections of 0-5 cm soil moisture for each grid cell. It also governs the redefinition of canopy cover categories based on crop calendar changes or local flooding conditions, and these categories are then used as input to the radar simulation program's target/sensor interaction model.

A.1 Storm Model

Daily rainfall measurements as reported by 25 stations located in and around the test site were used as the basis for the storm model. Figure A.2 shows the location of the test site. Table A.1 shows the daily rainfall reported at each of these stations for the simulation period; May 18 through June 9. A grid map of estimated rainfall, with a resolution of 3 km by 3 km, was produced from measured rainfall data at these irregularly spaced recording stations

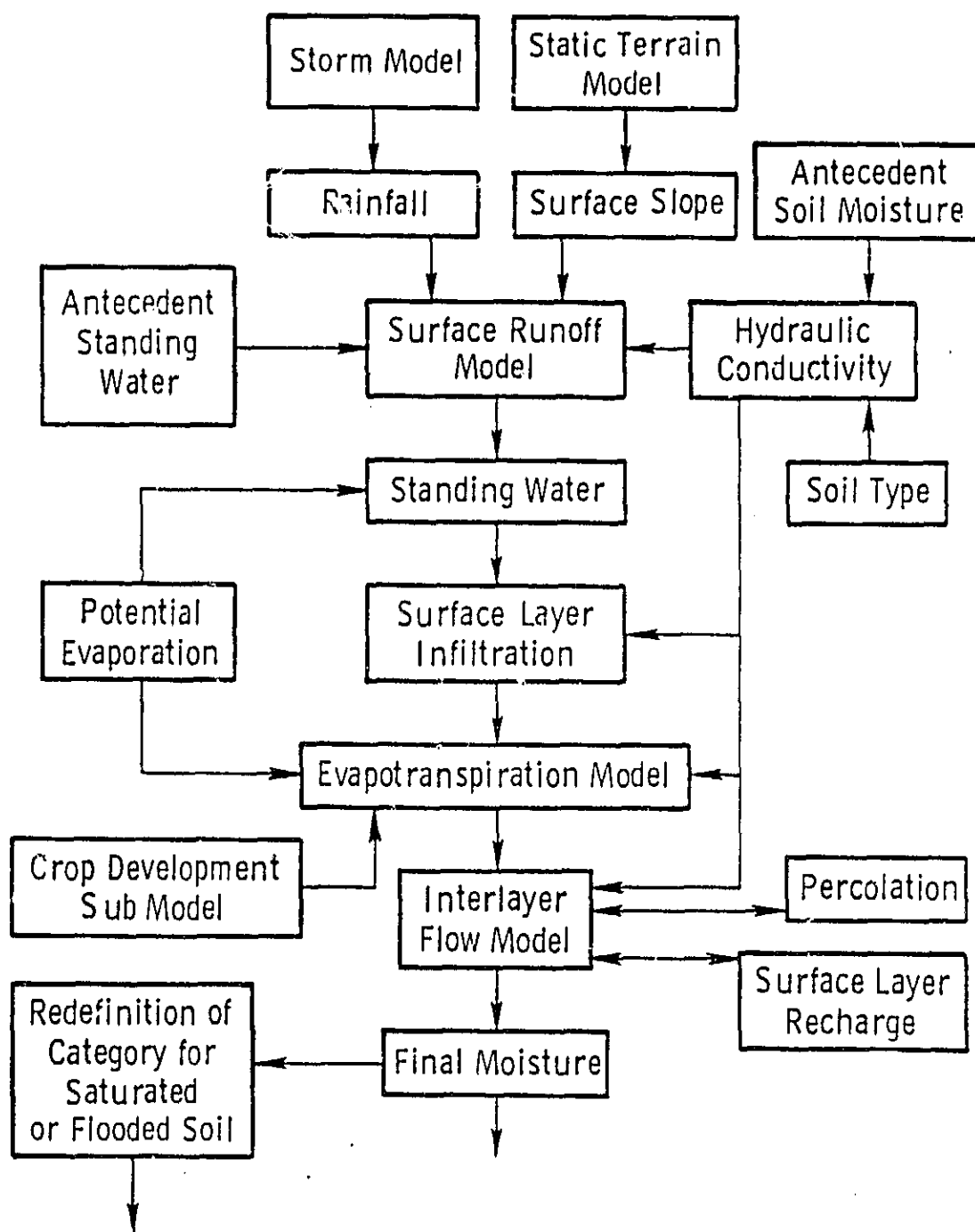


Figure A.1. Dynamic Soil Water Accounting Model (SWAM).

ORIGINAL PAGE IS
OF POOR QUALITY

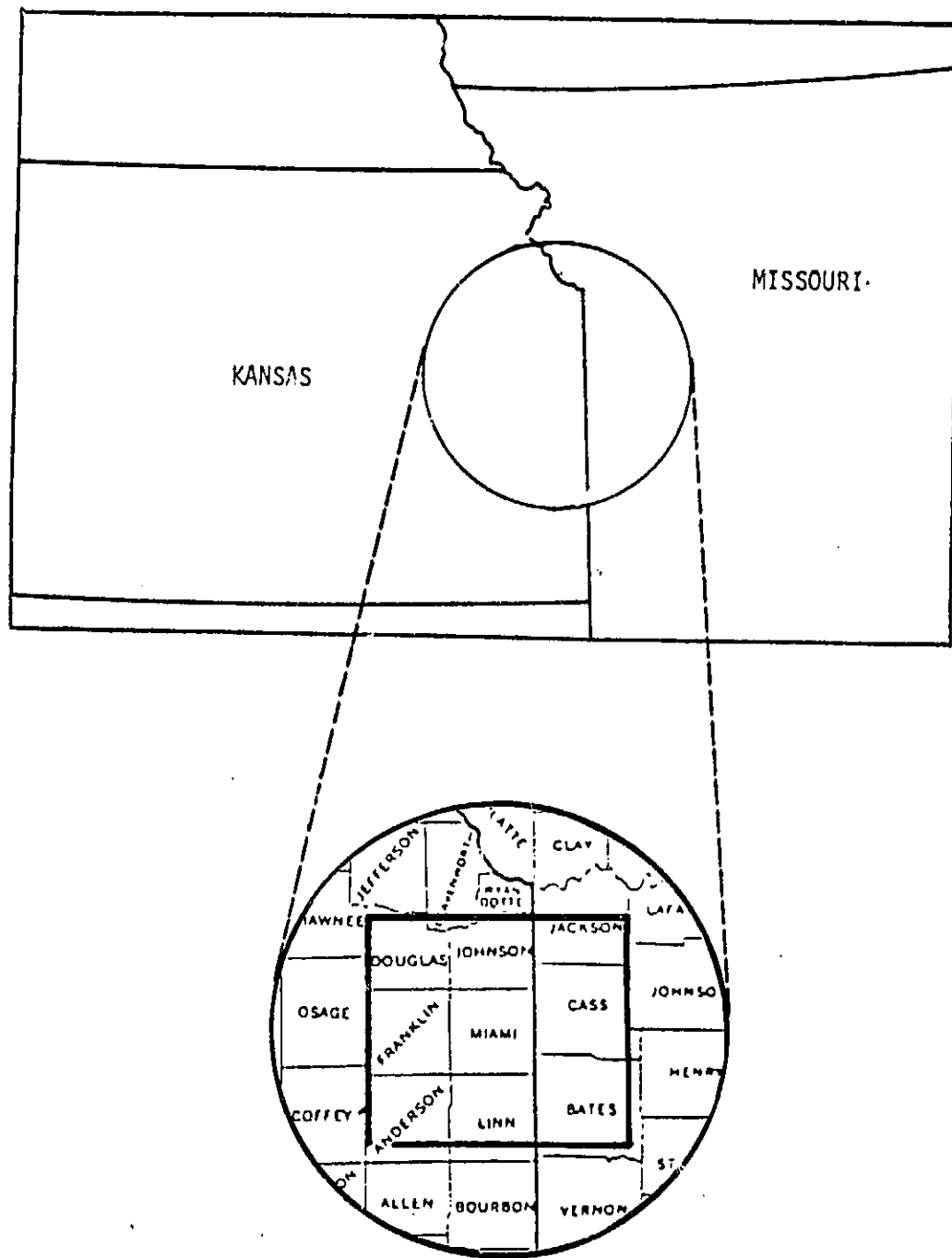


Figure A.2. Test site location.

ORIGINAL FROM IS
OF POOR QUALITY

| JULIAN DAY | TOPEKA USFO AF. | LEROY | HAUERLY | POMONA DAM | WILLIAMSBURG | LECOMPTON | CLINTON DAM | WORDEN | OTTAWA | GARNETT | LAURENCE | OSAWATOMIE | PAOLA | ROUND CITY | OLATHE | LACVONE | KANSAS CITY | STILLWELL | LEES SUMMIT | BUTLER | APPLETON CITY | ELDORADO SP. | ODESSA | LEXINGTON | CLINTON | CM | RAIN INCH | CM/HOUR |
|------------|-----------------|-------|---------|------------|--------------|-----------|-------------|--------|--------|---------|----------|------------|-------|------------|--------|---------|-------------|-----------|-------------|--------|---------------|--------------|--------|-----------|---------|------|--------------|---------|
| MAY 181 | 4.0 | 4.9 | 5.9 | 4.5 | 11.5 | 4.3 | 2.4 | 2.9 | 7.4 | 9.9 | 2.0 | 9.4 | 9.8 | 5.0 | 6.5 | 15.3 | 2.9 | 6.7 | 5.2 | 2.5 | 5.7 | 5.1 | 7.6 | 7.5 | 9.0 | 0.74 | 1.2 | |
| 182 | 1.9 | 5.1 | 1.9 | 0.4 | 1.7 | 1.7 | 2.7 | 2.2 | 1.3 | 8.0 | 2.5 | 0.9 | 2.3 | 0.2 | 1.5 | 1.1 | 0.1 | 2.0 | 1.4 | 11.0 | 0.1 | 0.5 | 1.7 | 1.0 | 0.6 | 0.31 | 1.7 | |
| 183 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.40 | | |
| 184 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 185 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 186 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 187 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 188 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 189 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 190 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 191 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 192 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 193 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 194 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 195 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 196 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 197 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 198 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 199 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 200 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 201 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 202 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 203 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 204 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 205 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 206 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 207 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 208 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 209 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 210 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 211 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 212 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 213 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 214 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 215 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 216 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 217 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 218 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 219 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 220 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 221 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 222 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 223 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 224 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 225 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 226 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 227 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 228 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 229 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 230 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 231 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 232 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 233 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 234 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 235 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 236 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 237 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 238 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 239 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 240 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 241 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 242 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 243 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 244 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 245 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 246 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 247 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 248 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 249 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 250 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 251 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 252 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 253 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 254 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 255 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 256 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 257 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 258 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 259 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |
| 260 | | | | | | | | | | | | | | | | | | | | | | | | | | 0.74 | | |

8 Epan : Mean of 11 stations for non-rainy days

Table A.1. Daily reported rainfall at 25 recording stations in and around the test site during the simulation period for 1981.

for every day during the simulation period that all or part of the test site received some rain. Figures A.3 and A.4 shows the amount of rain reported by each station on Julian day 144, and the estimated rainfall map for that day , respectively. These generated rainfall grid maps made available the total daily rainfall in cm received by each test site data base cell. An image representation of all rainfall grid maps has been shown on Figure 5.

Rainfall intensity is calculated as a daily constant from the minimum recorded daily storm duration according to

$$I_{\text{day}} = 10^{a_t} * D_{\text{day}}^{b_t} \quad (\text{A.1})$$

where

I_{day} = daily constant intensity, cm/hr

D_{day} = daily minimum recorded duration, hrs.

t = storm type (2-year or 5-year), and

a and b are constant for each storm type.

The constants a_t and b_t are solved from a plot of local rainfall intensity-vs-duration curves for recurrence intervals of 2 or 5 years. For each day of the simulation, a rainfall event is classified as either a 2-year or a 5-year event based upon the maximum recorded rainfall at all gauging stations on that day. If net daily rainfall at any gauge exceeds a critical value M , then that day will be classed as a 5-year event and a_t and b_t will be used from the 5-year intensity-vs-duration curve; otherwise a_t and b_t will be used for a 2-year event. M is defined by

$$M = 10^a * D^{b+1} / (b+1) \quad (\text{A.2})$$

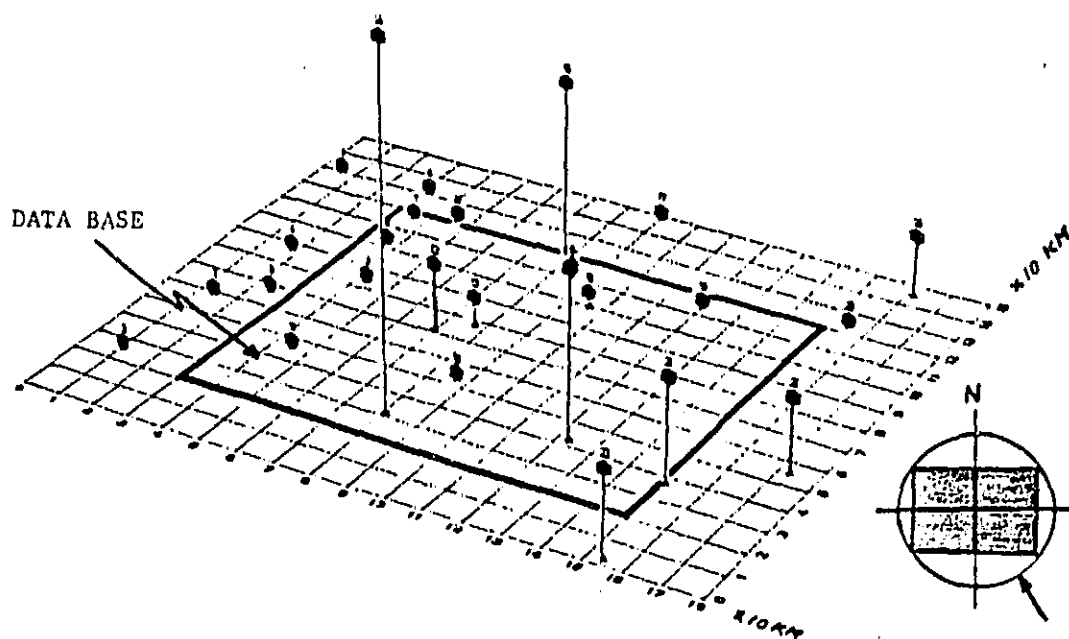


Figure A.3. Measured rainfall as reported on Julian day 144 at all stations in and around the data base (maximum rainfall is 4.8 cm).

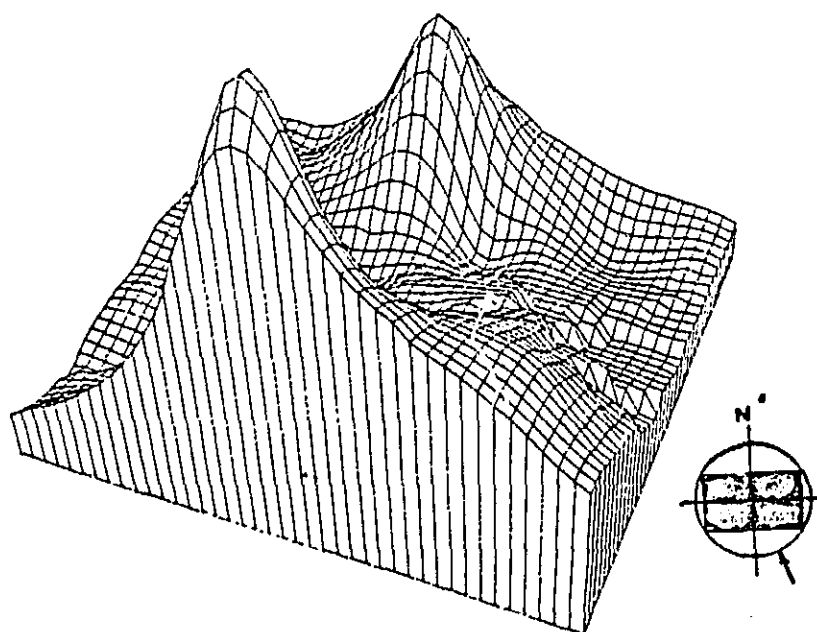


Figure A.4. Estimated rainfall on Julian day 144 for each 3 x 3 km area in the data base.

where a and b are 2-year coefficients. For the rainfall data given in Table A.1, the maximum net daily rainfall never exceeded M, therefore the 2-year coefficients were used in all precipitation events.

A.2 Surface Runoff Model

The surface runoff model considers only the net effect of local surface slope and does not explicitly account for water retention and impoundment by soil surface roughness, tillage practices, and the presence of terraces. The water available for drainage as lateral surface flow is equal to the sum of standing water remaining from the previous daily accounting period plus the incident rainfall in excess of that which can infiltrate the surface layer and the root layer. The drainage D is computed from remaining standing water and local surface slope by

$$D = SW * (1.1 - 0.8^{\alpha}) \quad (A.3)$$

where

SW = standing water

α = the slope angle of the surface from horizontal in degrees.

The term $1.1 - 0.8^{\alpha}$ is defined as the drainage coefficient and is plotted versus surface slope (in percent) in Figure A.5.

A.3 Evapotranspiration Model

Evapotranspiration is calculated differently for cropped

ORIGINAL PAGE IS
OF POOR QUALITY

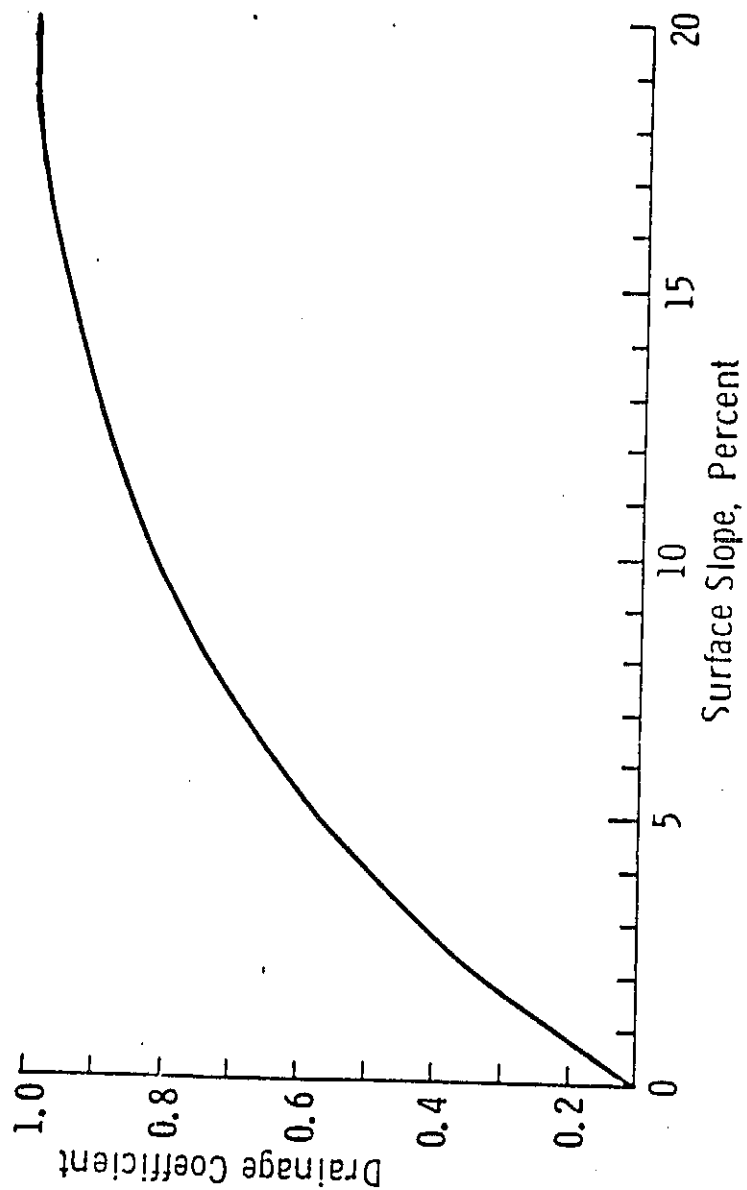


Figure A.5. Variation in drainage coefficient as a function of soil surface slope in the soil water accounting model (SWAN).

and bare soil surfaces. For bare soil surfaces, the actual evaporation is depleted solely from the soil surface layer, while for vegetated surfaces a static root distribution model removes 30 percent of the actual evapotranspiration from the 0-5-cm layer and removes the remaining 70 percent of actual evapotranspiration from the "root zone." For simplicity, the "root zone" is assumed to be one meter in depth and is treated as a constant with time and for all crops.

For bare soil, actual evaporation, AE, is computed from potential evaporation, PE, as limited by antecedent soil moisture in the surface layer and soil hydraulic properties. Accounting is performed on a daily basis using the mean daily pan evaporation recorded at 11 stations in the study area as shown in Table A.1 for 1981.

An experimental model is used to calculate actual evaporation from potential evaporation PE:

$$AE = PE * k_{\text{soil}} * k_{\text{storm}} \quad (\text{A.4})$$

where

$$k_{\text{storm}} = (24 - T)/24, \quad (\text{A.5})$$

k_{soil} = soil limiting coefficient

T = the duration of storm, and

$$PE = k_p * E_{\text{pan}}, \quad (\text{A.6})$$

where

k_p = pan coefficient, and

E_{pan} = measured pan evaporation.

The soil limiting coefficient k_{soil} is defined by an experimental model [16] dependent upon PE and soil

properties.

$$k_{\text{soil}} = A + B(\text{MR}) + C(\text{MR})^2 + D(\text{MR})^3 \quad (\text{A.7})$$

where A, B, C, and D are empirically derived coefficients dependent upon PE, and MR is the moisture ratio. Regression fits to experimental data yield [16]:

$$A = -0.05 + 0.732/\text{PE} \quad (\text{A.8})$$

$$B = 4.97 - 0.661 \text{ PE} \quad (\text{A.9})$$

$$C = -8.57 + 1.56 \text{ PE} \quad (\text{A.10})$$

$$D = 4.35 - 0.88 \text{ PE} \quad (\text{A.11})$$

The moisture ratio MR is related to soil water retention characteristics via

$$\text{MR} = (\theta - \text{WP})/(\text{FC} - \text{WP}) \quad (\text{A.12})$$

where

θ = measured soil moisture,

WP = soil moisture at wilting point, and

FC = soil moisture at field capacity.

Assuming wilting point and field capacity to be defined as matric potentials of 15 bars and 1/3 bars, respectively, WP and FC can be defined from soil textural components using the approach of Clapp and Hornberger [17]

$$\text{FC} = \theta_s (\psi_s/333)^{1/b}, \text{ and} \quad (\text{A.13})$$

$$\text{WP} = \theta_s (\psi_s/15,000)^{1/b} \quad (\text{A.14})$$

where

θ_s = soil moisture at saturation,

ψ_s = matric potential at saturation, and

b = an empirically derived value related to soil texture.

For a given soil, θ_s is calculated from the soil bulk density profile and ψ_s and b are defined by A-horizon soil texture using values given in [17]. Thus, for a given day, the terms in Eq. A.4 are dependent on the antecedent soil moisture and the gross water-retention characteristics of each soil.

For vegetated soil, the actual evapotranspiration, ET_{crop} , is computed by a modification of the Blaney-Criddle formulation used in estimating crop irrigation requirements [18,19]. Although the method is designed for an effective integration period of weeks to months, the simplicity of its input requirements makes this a practical approach for such a large number of coarse grid cells. Basically, crop consumption of water over the rooting depth varies with temperature, length of day, available soil moisture, crop type, crop stage of growth, relative humidity, and windspeed. To simplify the formulation, average measured values of temperature, day length, relative humidity, and windspeed are assumed on a seasonal basis for the simulation area. The resultant expression for ET_{crop} becomes:

$$ET_{crop} = PE * k_{crop} * k_{storm} \quad (A.15)$$

where

$$k_{crop} = \text{crop coefficient.}$$

Crop coefficient as adjusted for mean local climate is plotted in Figure A.6 as a function of number of days after planting for several of the crop covers included in the data base. Crop consumption of the water is seen to be dependent on both crop and stage of crop development. Before the crop

ORIGINAL PAGE IS
OF POOR QUALITY

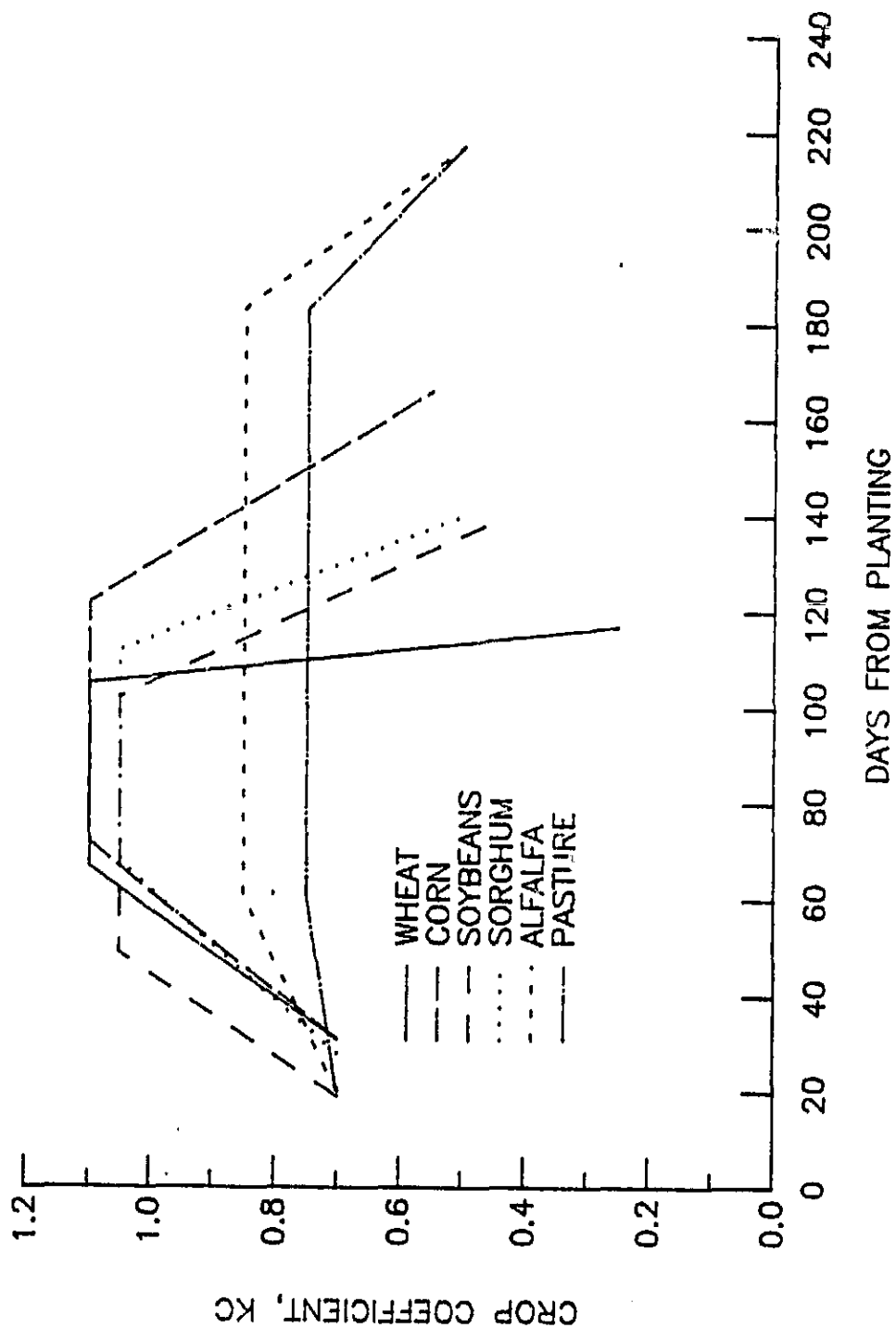


Figure A.6. Crop transpiration coefficient as a function of time from planting for several representative crops found within the simulation area.

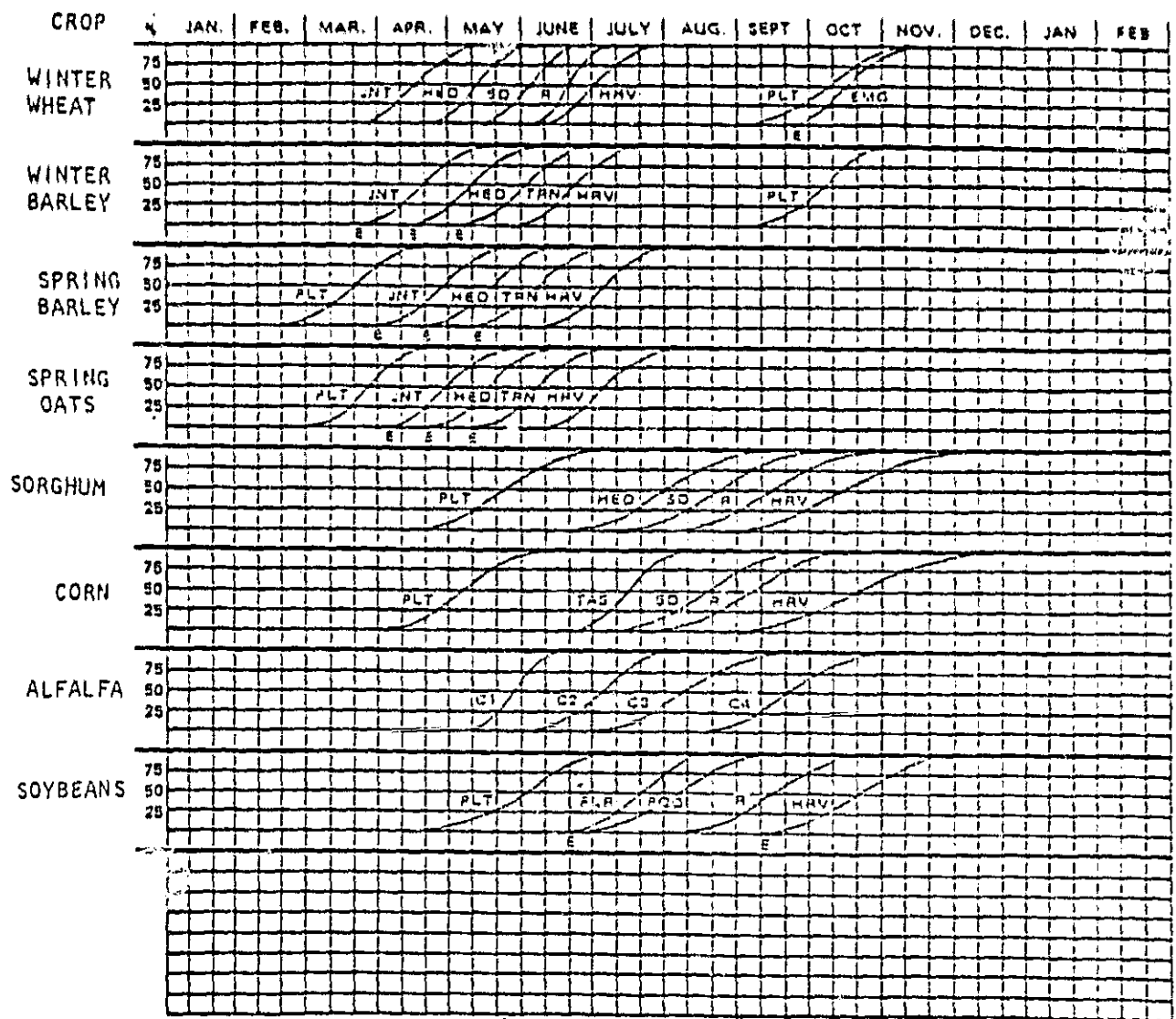
canopy has attained 20% ground coverage and again after harvest, the soil is treated as bare for both evapotranspiration and also for radar backscatter category.

A.4 Crop Development Model

The length of time required for a given agricultural field in the simulation data base to progress from one crop-development stage to the next is established from data gathered by the Statistical Reporting Service of the United States Department of Agriculture. The simulation area lies at the East Central reporting district of Kansas (No. 6). Figure A.7 presents a summary of mean crop development over a 10-year period as enumerated by AgRISTARS [20] for this crop reporting district. These percentages are used to define crop development stage within the simulation on a field-by-field basis. Thus, each distinct agricultural field in the data base is assigned one of the 10 planting dates. Hence, there are ten different absolute crop calendars possible for each crop type identified in Table 1.

Planting dates are randomly assigned to field codes for a specific crop based upon Figure A.7. This procedure results in the introduction of a significant source of between-field variance of soil moisture within a given crop type due to the effect of crop development stage on evapotranspiration. It also allows for a given field to have its target classification changed in Table 1, since a medium-rough bare field becomes a cropped field after

ONE-SIDED EFFECTS OF POOR QUALITY



| LEGEND | |
|--------|--|
| E | Under stage name, indicates rough estimate of date |
| EMG | Emergence |
| HED | Heading |
| HRV | Harvest |
| JNT | Jointing |
| PLT | Planting |
| R | Ripe |
| SD | Soft dough |
| TRN | Turning |
| FLR | Flowering |
| C | Cut |
| TAS | Tasseling |

Figure A.7. Percent of crop are in development stage by specified date for Kansas crop reporting district 6 average crop calendars from 1963 to 1973 [20].

emergence, and finally reverts to bare soil status after harvest. As implemented, this procedure gives the data base a dynamic crop-category mix that can be modified to match regional agricultural practices such as double-cropping or dynamic soil surface roughness conditions.

A.5 Interlayer Water Redistribution

Infiltration of water into the surface layer, percolation of water into the root zone, and capillary recharge of surface layer moisture are controlled by the matric-potential profile as limited by soil structure.

A pixel's infiltration capacity during rainfall is given by [21]

$$i_r = t^{1/2} [2 k_s \psi_f(\theta_s - \theta)]^{1/2} + k_s t/2 \quad (\text{A.16})$$

where

t = duration of rain event, hrs.

k_s = hydraulic conductivity at saturation

ψ_s = suction at field capacity

θ_s = porosity = $1 - \rho_b/\rho_s$

ρ_b = soil bulk density, g/cm³

ρ_s = soil specific density = 2.65 g/cm³ for all soils.

After rainfall ceases, infiltration proceeds at a rate defined by $k_s/2$ for the remaining time of the accounting period (24-t) or until all standing water is depleted. Thus, a pixel's infiltration capacity from standing water is defined as

$$i_{sw} = k_s/2 * (24 - t) \quad (\text{A.17})$$

and is limited by the amount of standing water. Hence, total infiltration into the surface layer of the soil, i_t , is determined by

$$i_t = i_r + i_{sw} \quad (A.18)$$

where

i_r < total rainfall received by the pixel

i_{sw} < standing water available.

Water will percolate from the surface layer (0-5-cm) into the root zone for all accounting periods where the surface layer's water content after infiltration exceeds the water content at field capacity (as determined by Equation A.13), such that final surface-layer's water content is reduced to less than porosity.

This is accomplished by first allowing excess water to drain from the root zone (5-100 cm depth). One third of the volumetric moisture in excess of root zone field capacity is allowed to drain gravitationally each day and hence is removed from further accounting periods. Then, assuming that the water content in the surface layer exceeds field capacity, the excess is permitted to percolate into the root zone at the minimum of either

$$R_i = \frac{T k_s}{2\alpha} \quad (A.19)$$

where

R_i = net percolation into the root zone,

α = a damping coefficient arbitrarily set to 48, and

T = duration of accounting period = 24 hours
or 1/3 of excess water is allowed to percolate

$$R_1 = (\theta - FC)/3 \quad (A.20)$$

where θ and FC are for the surface layer.

When evapotranspirative losses cause surface-layer water content to be reduced below wilting point, capillary recharge of the surface 5 cm of soil is allowed to occur during the night for a duration of 12 hours. The rate of the surface recharge is equal to $k_s/2$ and is arbitrarily limited to a maximum of 0.25 cm of water. Furthermore, capillary recharge is not allowed to raise surface layer water content above wilting point.

A.6 Within-Field Variability in Surface Soil Moisture

Prior to radar image simulation, the surface layer soil moisture values determined by the water-budget model for each 100-m by 100-m grid cell are randomized to approximate the natural variability in soil moisture measured within "homogeneous" fields. Randomization was performed on a grid-cell basis by a Gaussian random-number generator with a standard deviation of 6 percent M_{fs} [2].

A.7 Generation of Soil Moisture Distributions

The dynamic soil water accounting model (SWAM) was initialized on Julian day 138 and moisture distribution maps of the test site were produced for every day of the simulation period.

These moisture maps indicated the percent of the 1/3-bar water content M_{fs} in the 0-5 cm layer where

$$M_{fs} = 100 \times \theta/FC \quad (A.21)$$

where

θ = measured soil moisture

FC = soil moisture at field capacity.

The resultant distributions were then examined and the three most closely approximating moderately dry, moist, and wet soil surface conditions were selected for radar image simulation. Image representation of 0-5-cm soil moisture distribution for Julian day 141, 150 and 160 are shown on Figure 6.

DEFINITIONS

| | |
|-----------|--|
| PAUSDATE | An array which contains the Julian days on which the output moisture map needs to be saved. |
| STRDATE | Julian day on which the process should begin. |
| STOPDATE | Julian day on which the process should stop. |
| RAINDATE | An array containing the Julian dates which all or part of the database received some rain. |
| ALLINTS | An array containing the mean rain intensity of each rainy day. |
| RAIN | Amount of rain received by a cell on a certain day in cm. |
| INTENSITY | Intensity of the rain for a cell in cm/hour. |
| DUR | Duration of the rain for a cell in hours |
| PERCENTS | In soil data subroutine. An array of percent probability of occurrence of soil bulk density associated with each of eight soil types present in our data base. |
| SFBULK | Quantized levels of surface layer (0-5 cm) bulk density associated with "PERCENTS". |
| RTBULK | Quantized levels of root layer (5-100 cm) bulk density associated with "PERCENTS". |
| B | An array containing b values for all 15 soil textures as estimated from Clapp & Hornberger, 1978. |
| FSUCTION | An array containing the suction ψ_f (at field capacity) for all 15 soil textures (see Clapp & Hornberger, 1978). |
| SSUCTION | An array containing the suction ψ_s (at saturation) for all 15 soil textures. |
| SHYDCOND | An array containing the hydraulic conductivity at saturation k_s for all 15 soil textures. |

| | |
|----------|---|
| SATHC | Hydraulic conductivity at saturation. |
| PDATES | An array containing ten different planting dates for each crop type. |
| STAGEDAY | An array containing the number of days after the planting date which the crop advances to a new crop growth stage (five different stages) for each crop type. |
| KEQCONST | An array containing two parameters (slope and intercept) describing the change in K_{CROP} at each stage and for each crop type. |
| KCROP | Crop transpiration coefficient. |
| SW | Standing water (cm). |
| SWINF | Amount of standing water which infiltrates to the surface layer (cm). |
| RAININF | Amount of rain which infiltrates to the surface layer. |
| MPC | Water content expressed as a percent of field capacity. |
| DRAIN | Amount of excess water which is drained from the root zone (cm/cm). |
| SWRUNOFF | Amount of water runoff from standing water (cm). |
| RECHRG | Capillary recharge (cm). |
| ETO | An array containing the potential evaporation (cm) for every day of the simulation period. |
| SWEVAP | Amount of evaporation from standing water. |
| KSOIL | Bare soils evaporation coefficient. |

The following variables are prefixed by "SF" or "RT" indicating the surface layer (0-5 cm) or root zone (5-100 cm), respectively.

| | |
|------|--|
| BD | soil's bulk density |
| PROS | soil's porosity |
| FC | soil's water content at field capacity (cm/cm) |
| WP | soil's water content at wilting point (cm/cm) |
| WC | water content (cm/cm) |
| EVAP | amount of evaporation (cm) |

ORIGINAL PAGE IS
OF POOR QUALITY.

```

1 C -----
2 C UNIVERSITY OF KANSAS REMOTE SENSING LAB
3 C -----
4 C PROGRAM SUITE : RADAR SIMULATION REF. # : RSL REPORT 601-1
5 C -----
6 C PROGRAM NAME: SUAM AUTHOR: SAIED MOEZZI DATE: MAY 1983
7 C LANGUAGE : FORTRAN 77
8 C -----
9 C PURPOSE : THE PURPOSE OF PROGRAM SUAM (SOIL WATER ACCOUNTING MODEL)
10 C IS TO GENERATE A DISRIBUTION OF NEAR-SURFACE (0-5 CM) SOIL MOISTURE
11 C CONDITION AT THE SPATIAL SCALE OF THE STATIC TERRAIN DATA BASE WHICH
12 C RESPONDS TO BOTH STATIC CONDITIONS (SOIL TYPE, COVER TYPE, AND SURFACE
13 C SLOPE) AND DYNAMIC CONDITIONS (CROP STAGE, RAIN, AND POTENTIAL EVAPO-
14 C RATION) ON A DAILY BASIS.
15 C -----
16 C
17 C PARAMETER DEFINITION
18 C NAME DESCRIPTION
19 C -----
20 C IROW1 FIRST ROW OF THE INPUT MATRIX TO BE PROCESSED
21 C IROW2 LAST ROW OF THE INPUT MATRIX TO BE PROCESSED
22 C ICOL1 FIRST COLUMN CELL OF THE INPUT ROWS TO BE PROCESSED
23 C ICOL2 LAST COLUMN CELL OF THE INPUT ROWS TO BE PROCESSED
24 C IOTCOL NUMBER OF CELLS IN EACH OUTPUT ROW
25 C NCOL NUMBER OF CELLS IN EACH INPUT ROW
26 C NPAUSE NUMBER OF TIMES THAT PROGRAM SHOULD PAUSE DURING
27 C SIMULATION PERIOD FOR SAVING THE MOISTURE MAP
28 C -----
29 C
30 C SUBROUTINES REQUIRED
31 C NAME DESCRIPTION
32 C -----
33 C RAINFALL RETURNS THE AMOUNT OF RAIN (CM), DURATION (HOURS) AND
34 C INTENSITY ( CM/HOUR ) FOR A GIVEN CELL ON A SPECIFIED
35 C JULIAN DAY.
36 C INTRLAYR THIS ROUTINE CONTAINS ALL 4 WATER ACCOUNTING MODELS
37 C EACH AS A SEARATE ENTRY. THESE ENTRIES ARE : SURFINF,
38 C ROOTINF, RUNOFF AND RECHARGE.
39 C INITIALZ THIS ROUTINE IS USED FOR INITIALIZATION PROCESS AND
40 C HAS TWO ENTRIES. THESE ARE: COMMENCE AND DAWN.
41 C EVAPORAT THIS ROUTINE SIMULATES THE EVAPORATION PROCESS FOR A
42 C GIVEN CELL ON A SPECIFIED JULIAN DAY.
43 C CELLDATA THIS ROUTINE GETS ALL STATIC CONDITIONS OF A GIVEN
44 C DATA BASE CELL.
45 C CROPDATA THIS ROUTINE GETS THE DYNAMIC CONDITIONS OF A GIVEN
46 C DATA BASE CELL WHICH IS REGISTERED AS A CROP TYPE.
47 C SOILDATA THIS ROUTINE GET ALL THE REQUIRED INFORMATION
48 C THAT IS BASED ON THE SOIL TYPE FOR A GIVEN CELL.
49 C GETFILES THIS ROUTINE OPENS ALL THE INPUT AN OUTPUT FILES.
50 C IOCALLS THIS ROUTINE CONTAINS TWO ENTRIES FOR READING AND
51 C WRITING INPUT AND OUTPUT RECORDS. THESE ARE: READREC,
52 C AND WRITDATA.
53 C UPDTHIST THIS ROUTINE IS USED FOR UPDATING A GIVEN HISTIGRAM.
54 C OPTHIST THIS ROUTINE IS USED FOR WRITING OUT A GIVEN
55 C HISTOGRAM.
56 C COPNFIL EXTERNAL FUNCTION CALLED BEY 'GETFILES' ROUTINE
57 C -----
58 C
59 C
60 C
61 C PARAMETER ( IROW1=1,IROW2=1077,ICOL1=1,ICOL2=1245,IOTCOL=1245 )
62 C PARAMETER ( NPAUSE=4 , NCOL=1245 )
63 C
64 C
65 C INTEGER PAUSDATE( NPAUSE ), FC( 14 ), HHMMSS( 3 )
66 C INTEGER WATER, SOIL, ELEV, CATG, CAT, COL, ROW, DATE
67 C INTEGER STRTDATE, STOPDATE, CROP, FIELD, DAY
68 C REAL KCROP, INTNSITY, MFC
69 C CHARACTER*8 TYPE, TYPENOW
70 C LOGICAL PAUSE

```

ORIGINAL PAGE IS
OF POOR QUALITY

```

71      COMMON /BUF3/ MFCOUT( NPAUSE, NCOL ), ICATOUT( NPAUSE, NCOL )
72      SPECIAL COMMON BUF3
73      COMMON /BUF4/ MFCHIST( NPAUSE , 256 ), ICATHIST( NPAUSE , 31 )
74      SPECIAL COMMON BUF4
75      COMMON /BLOCK/
76      & SATHC, SUCTION, SFPROS, RTPROS, SFFC, RTFC, SFUP,
77      & SU, SFUC, RTUC, KCROP,
78      & DAY, RAIN, DUR, INTENSITY, SLOPE, TYPENOW
79      COMMON /FILCOD/ FC
80      DATA WATER/ 10 /, STRTDATE/ 138 /, STOPDATE/ 160 /
81      DATA PAUDDATE/ 140, 141, 150, 160 /
82 C
83 C
84 C
85      WRITE(13,101) IROW1, IROW2, ICOL1, ICOL2
86 C
87 C      INITIALIZE ALL NECESSARY VARIABLES
88 C
89      CALL COMMENCE
90 C
91 C      PROCESS EVERY CELL IN THE DATA BASE
92 C
93      FOR ROW=IROW1, IROW2
94 C
95 C      AFTER PROCESSING EVERY 100 RECORDS SEND A MESSAGE TO TO TERMINAL
96 C
97      IF( MOD(ROW,10) .EQ. 0 ) THEN
98      CALL TIME(HHMMSS)
99      WRITE(11,103) ROW, HHMMSS
100     END IF
101     FOR COL=ICOL1, ICOL2
102 C
103 C      GET REQUIRED INFORMATIONS FOR THE CELL BEING PROCESSED
104 C
105     CALL CELLDATA( ROW,COL,ELEV,SOIL,CATG,SLOPE,TYPE,CROP,FIELD )
106     IF( TYPE .EQ. 'NONAGRIC' ) THEN
107 C
108 C      THIS IS NOT AN AGRICULTURAL CELL THEREFORE SHOULD NOT BE
109 C      TREATED IN MOISTURE COMPUTATION. UPDATE THE OUTPUT ROW AND
110 C      START WITH NEXT CELL IN THE DATA BASE.
111 C
112     FOR IP=1, NPAUSE
113     MFCOUT( IP , COL ) = 0
114     ICATOUT( IP , COL ) = CATG
115     CALL UPDTHIST( 0 , MFCHIST, IP, 0, 250 )
116     ICAT = CATG / 10
117     CALL UPDTHIST( ICAT, ICATHIST, IP, 0, 25 )
118     END FOR
119     ELSE
120 C
121 C      ELSE THIS CELL IS AN AGRICULTURAL TYPE, START THE MOISTURE
122 C      COMPUTATION AND CONTINUE FOR THE ENTIRE SIMULATION PERIOD.
123 C
124 C      GET MORE INFORMATION ABOUT THE UNDERLAYING SOIL
125 C
126     CALL SOILDATA( SOIL, SFPROS, RTPROS, SFFC, RTFC, SFUP,
127     & SATHC, SUCTION )
128 C
129 C      INITIALIZE THIS CELL'S MOISTURE FOR DAY ZERO
130 C
131     CALL DAWN
132 C
133     FOR DATE= STRTDATE, STOPDATE
134 C
135     DAY = DAY + 1
136 C
137 C      IF IT IS A RAINY DAY, THEN GET AMOUNT, INTENSITY AND THE
138 C      DURATION OF THE RAINFALL ON THIS GROUND CELL BEING PROCESSED
139 C
140     CALL RAINFALL( DATE, ROW, COL, RAIN, INTENSITY, DUR )

```


GROUND WATER QUALITY

```

141 C
142 C IF THE GROUND CELL IS REGISTERED AS A CROP THEN GET
143 C KCROP AND CROP STAGE
144 C
145 C IF( TYPE .EQ. 'CROP ' ) THEN
146 C CALL CRODATA( CROP, FIELD, DATE, KCROP, TYPENOW )
147 C END IF
148 C
149 C
150 C PROCESS ALL SOIL WATER ACCOUNTING MODELS
151 C
152 C 1: PONDING AND INFILTRATION INTO THE SURFACE LAYER (0 - 5 CM)
153 C
154 C CALL SURFINFL
155 C
156 C 2: PERCOLATION OF WATER INTO THE ROOT ZONE (5 - 95 CM)
157 C
158 C CALL ROOTINFL
159 C
160 C 3: STANDING WATER RUNOFF DUE TO LOCAL SLOPE
161 C
162 C CALL RUNOFF
163 C
164 C 4: EVAPOTRANSPIRATION
165 C
166 C CALL EVAPORAT
167 C
168 C 5: CAPILLARY RECHARGE OF THE SURFACE LAYER
169 C
170 C CALL RECHARGE
171 C
172 C
173 C COMPUTE % OF FIELD CAPACITY OF SOIL MOISTURE BASED ON SURFACE
174 C LAYER'S WATER CONTENT
175 C MFC = 100.0 * SFWC / SFFC
176 C
177 C
178 C
179 C CHECK TO SEE IF THIS IS A PAUSE DAY, IF IT IS THEN RECORD
180 C THE COMPUTED 'MFC' AND THE REASSIGNED CATEGORY.
181 C (PAUSE DAY IS THE DAY THAT THE MOISTURE MAP MUST BE SAVED)
182 C
183 C PAUSE = .FALSE.
184 C FOR IP=1, NPAUSE
185 C IF( DATE .EQ. PAUSDATE( IP ) ) THEN
186 C PAUSE = .TRUE.
187 C GOTO 100
188 C END IF
189 C END FOR
190 C IF( PAUSE ) THEN
191 C
192 C APPLY A GAUSSIAN DISTRIBUTION WITH COMPUTED 'MFC' AS THE
193 C MEAN, AND 6% MFC AS THE STANDARD DIVIATION
194 C
195 C IMFC = NINT( RANN( MFC , 6.0 ) )
196 C
197 C SET LOWER LIMIT OF % FIELD CAPACITY TO ONE
198 C
199 C IF( IMFC .LT. 1 ) IMFC=1
200 C
201 C SAVE COMPUTED 'MFC' FOR THIS PAUSE DAY
202 C
203 C MFCOUT( IP , COL ) = IMFC
204 C
205 C REASSIGNMENT OF THE REGISTERED CELL'S CATEGORY
206 C 1: CHANGE THE CATEGORY TO WATER IF THERE IS STANDINNG WATER
207 C ON THIS GROUND CELL
208 C 2: CHANGE THE CATEGORY TO WATER IF SURFACE LAYER'S WATER
209 C CONTENT EXCEEDS THE UNDERLAYING SOIL'S PROSITY
210 C 3: IF THERE IS NO STANDING WATER AND CELL IS REGISTERD AS A

```

CROPS OF POOR QUALITY

```

211 C      CROP TYPE, THEN CHANGE THE CATEGORY TO BARE SOIL WHEN
212 C      BEFORE EMERGENCE OF THE CROP OR AFTER HARVEST
213 C
214       IF( SW .GT. 0 ) THEN
215       CAT = WATER
216       ELSE
217       IF( SFWC .LT. SFPROS ) THEN
218       CAT = CATG
219       IF((TYPE.EQ.'CROP'   ) .AND.(TYPENOW.EQ.'SMTHBARE')) CAT = 210
220       IF((TYPE.EQ.'CROP'   ) .AND.(TYPENOW.EQ.'MEDMBARE')) CAT = 200
221       ELSE
222       CAT = WATER
223       END IF
224       END IF
225       ICATOUT( IP , COL ) = CAT
226       ICAT = CAT / 10
227 C
228 C      UPDATE THE HISTOGRAMS
229 C
230       CALL UPDTHIST( IMFC, MFCHIST, IP, 0, 250 )
231       CALL UPDTHIST( ICAT, ICATHIST, IP, 0, 25 )
232 C
233       END IF
234       END FOR
235 C
236 C      DONE WITH MOISTURE ESTIMATION FOR THIS CELL
237 C
238       END IF
239       END FOR
240 C
241 C      DONE WITH ALL THE COLUMNS OF THIS ROW
242 C      WRITE OUT THE COMPUTED MFC AND THE REASSIGNED CATEGORIES OF THIS
243 C      ROW TO THE OUTPUT FILES FOR ALL PAUSE DATES.
244 C
245       CALL WRITDATA( 1, MFCOUT, IOTCOL )
246       CALL WRITDATA( 2, ICATOUT, IOTCOL )
247 C
248       END FOR
249 C
250 C      SOIL MOISTURE ESTIMATION IS DONE FOR THE ENTIRE DATA BASE
251 C      WRITE OUT A REPORT OF THE FINAL MOISTURE AND CATEGORY MAPS
252 C
253       FOR IP=1, NPAUSE
254       WRITE(13,104) ' MFC ', PAUSDATE( IP )
255       CALL OPTHIST( MFCHIST, IP, 0, 250 )
256       WRITE(13,104) 'CATEGORY', PAUSDATE( IP )
257       CALL OPTHIST( ICATHIST, IP, 0, 25 )
258       END FOR
259       CALL TIME(HHMMSS)
260       WRITE(13, '( * COMPLETED AT ', 3A3) ) HHMMSS
261       WRITE(11, '( * COMPLETED AT ', 3A3) ) HHMMSS
262       WRITE(11,102)
263       WRITE(13,102)
264       STOP
265 101  FORMAT(///, ' S O I L   W A T E R   A C C O U N T I N G ',
266      & '   P R O G R A M'///, ' SWAM WAS PROCESSED ON THE DATA BASE'///
267      & ' ROW'IS, ' THROUGH ROW'IS, ' , COL'IS' THROUGH COL'IS)
268 102  FORMAT(' * * * A L L   D O N E * * *')
269 103  FORMAT(' P R O C E S S E D   T H R O U G H   R E C O R D ', 5X, I4,
270      & 3X, 3A3)
271 104  FORMAT('1', A8, ' H I S T O G R A M   F O R   J U L I A N   D A Y 'IS)
272  END

```

```

273 C
274 C
275 C-----RAINFALL
276 C
277 C
278 C      THIS ROUTINE READS THE RAINFALL DATA AND RETURNS THE AMOUNT
279 C      OF RAIN, DURATION, AND INTENSITY FOR A GIVEN CELL WITHIN THE
280 C      DATA BASE ON A SPECIFIED JULIAN DAY.
281 C      RAIN IS IN UNITS OF CENTIMETERS , INTENSITY IS IN CM/HOUR,
282 C      AND DURATION IS IN HOURS.
283 C
284 C
285 C      SUBROUTINE RAINFALL( DATE, DBROW, DBCOL, RAIN, INTNSITY, DUR )
286 C      IMPLICIT INTEGER ( A - Z )
287 C      PARAMETER ( NDAY=13 , NRCOL=42 )
288 C      COMMON /BUFS/ ROWRAIN( NRCOL,NDAY), RAINDATE( NDAY)
289 C      SPECIAL COMMON BUFS
290 C      DIMENSION FC(14)
291 C      COMMON /FILCOD/ FC
292 C      REAL RAIN, DUR, INTNSITY, ALLINTS( NDAY )
293 C      DATA RECPTR / 0 /
294 C      DATA RAINDATE
295 C      & / 138,139,143,144,148,149,150,151,153,154,155,159,161 /
296 C      DATA ALLINTS
297 C      & / 1.2,1.7,1.7,3.6,2.3,2.3,3.6,1.4,3.6,3.6,3.6,2.3,2.3 /
298 C
299 C
300 C
301 C      READ RAINFALL DATA FOR ALL RAINY DAYS FOR THIS GROUND CELL
302 C
303 C      RAINROW = ( ( DBROW - 1 ) / 30 + 1 )
304 C      RAINCOL = ( ( DBCOL - 1 ) / 30 + 1 )
305 C      WHILE( RECPTR .LT. RAINROW )
306 C      FOR COL=1, NRCOL
307 C      READ( FC(5), IOSTAT=IOS) ( ROWRAIN(COL,DAY), DAY=1, NDAY )
308 C      IF( IOS .NE. 0 ) GOTO 99
309 C      END FOR
310 C      RECPTR = RECPTR + 1
311 C      END WHILE
312 C
313 C
314 C
315 C      CHECK IF THE DATE GIVEN WAS A RAINY DAY
316 C
317 C      FOR DAY=1, NDAY
318 C      IF( RAINDATE( DAY ) .EQ. DATE ) GOTO 10
319 C      END FOR
320 C
321 C      NO STORM ON THIS DAY, RETURN TO THE CALLING PROGRAM
322 C
323 C      RAIN = 0.
324 C      INTNSITY = 0.
325 C      DUR = 0.
326 C      RETURN
327 C
328 C      A STORM OCCURED ON THIS DAY, GET THE AMOUNT OF RAIN RECIEVED
329 C      BY THIS CELL ON THE GIVEN JULIAN DAY
330 C
331 C      RAIN = REAL( ROWRAIN( RAINCOL, DAY ) ) / 10.0
332 C      INTNSITY = ALLINTS( DAY )
333 C      DUR = RAIN / INTNSITY
334 C      RETURN
335 C
336 C      99 WRITE(11, '(1X, "ERROR **** WHILE READING RAINFALL "') )
337 C      STOP
338 C      END

```

ROUTINE INTRLAYR OF POOR QUALITY

```

339 C
340 C
341 C-----INTRLAYR
342 C
343 C
344 C      THIS ROUTINE CONTAINS ALL 4 WATER ACCOUNTING MODELS, EACH
345 C      AS A SEPARATE ENTRY. THESE ARE 1-SURFACE INFILTRATION,
346 C      2-ROOT INFILTRATION, 3-RUNOFF, 4-RECHARGE
347 C
348 C      SUBROUTINE INTRLAYR
349 C
350 C      INTEGER      FC( 14 ), DAY
351 C      REAL          KCROP, INTNSITY, MAXRTINF, MINRTINF
352 C      CHARACTER*8   TYPENOW
353 C      COMMON /BLOCK/
354 C      & SATHC, SUCTION, SFPROS, RTPROS, SFEC, RTFC, SFUC,
355 C      & SW, SFUC, RTUC, KCROP,
356 C      & DAY, RAIN, DUR, INTNSITY, SLOPE, TYPENOW
357 C      COMMON /FILCOD/ FC
358 C
359 C      ENTRY SURFINFL
360 C      -----
361 C
362 C      COMPUTE AMOUNT OF 'RAIN' WHICH INFILTRATES TO SURFACE LAYER
363 C
364 C      IF( RAIN .GT. 0 ) THEN
365 C      RI = SQRT( DUR ) * SQRT( 2*SATHC*SUCTION*( SFPROS-SFUC ) ) +
366 C          SATHC * DUR / 2
367 C      RAININF = AMINI( RAIN , RI )
368 C      SW = SW + ( RAIN - RAININF )
369 C      ELSE
370 C      RAININF = 0
371 C      END IF
372 C
373 C      COMPUTE AMOUNT OF 'STANDING WATER' WHICH INFILTRATES TO SURFACE
374 C      LAYER AFTER RAINFALL CEASES
375 C
376 C      IF( SW .GT. 0 ) THEN
377 C      SUI = SATHC * ( 24 - DUR ) / 2
378 C      SWINF = AMINI( SW , SUI )
379 C      SW = SW - SWINF
380 C      ELSE
381 C      SWINF = 0
382 C      END IF
383 C
384 C      TOTALINF = RAININF + SWINF
385 C
386 C      COMPUTE WATER CONTENT PER CENTIMETER OF SURFACE LAYER
387 C
388 C      SFUC = SFUC + TOTALINF / 5.0
389 C      RETURN
390 C
391 C      ENTRY ROOTINFL
392 C      -----
393 C
394 C      COMPUTE PERCOLATION OF WATER FROM THE SURFACE LAYER INTO
395 C      THE ROOT ZONE ( 5-100 CM )
396 C
397 C      FIRST DRAIN THE EXCESS WATER OUT OF ROOT LAYER
398 C
399 C      IF( RTUC .GT. RTFC ) THEN
400 C      DRAIN = (RTUC - RTFC) / 3
401 C      RTUC = RTUC - DRAIN
402 C      END IF
403 C
404 C      THEN PERCOLATE

```

OF POOR QUALITY

```

409 C
410 IF( SFUC .GT. SFFC ) THEN
411 SFUC1 = SFUC
412 RTINF1 = 0.25 * SATHC
413 RTINF2 = (SFUC - SFFC) / 3
414 SFUC = AMIN1( SFUC1 , SFPROS )
415 SFUC = AMAX1( SFUC-RTINF2 , SFUC1-RTINF1 )
416 RTINF = (SFUC1 - SFUC) * 5
417 RTUC = RTUC + RTINF/95
418 ELSE
419 RTINF = 0
420 RETURN
421 END IF
422 C
423 C NOW CHECK THE SURFACE WATER CONTENT, IF IT EXCEEDS THE
424 C PROSITY OF THE SOIL TYPE MOVE THE EXCESS WATER TO THE
425 C STANDING WATER
426 C
427 IF( SFUC .GT. SFPROS ) THEN
428 SWADD = ( SFUC - SFPROS ) * 5
429 SFUC = SFPROS
430 SW = SW + SWADD
431 END IF
432 C
433 C RETURN
434 C
435 C ENTRY RUNOFF
436 C -----
437 C
438 C
439 C
440 C COMPUTE RUNOFF CAUSED BY THE SLOPE FOR "STANDING WATER"
441 C
442 IF( SW .GT. 0 ) THEN
443 SURUNOFF = SW * ( 1.1 - 0.8 *SLOPE )
444 SW = AMIN1( SW , SW-SURUNOFF )
445 ELSE
446 SURUNOFF = 0.
447 END IF
448 RETURN
449 C
450 C
451 C ENTRY RECHARGE
452 C -----
453 C
454 C CAPILLARY RECHARGE IS ALLOWED TO OCCURE DURING NIGHT FOR A
455 C DURATION OF 12 HOURS
456 C
457 IF( SFUC .LT. SFUP ) THEN
458 SFUC1 = SFUC
459 RECHRG = 0.25
460 SFUC = SFUC1 + RECHRG/5
461 IF( SFUC .GT. SFUP ) THEN
462 SFUC = SFUP
463 RECHRG = (SFUC - SFUC1) * 5
464 END IF
465 RTUC = ( 95 * RTUC - RECHRG ) / 95
466 ELSE
467 RECHRG = 0
468 END IF
469 C
470 RETURN
471 END

```

ORIGINAL PAGE 19
OF POOR QUALITY

~~ORIGINAL PAGE 19
OF POOR QUALITY~~

```

472 C
473 C
474 C-----INITIALZ
475 C
476 C
477 C      THIS ROUTINE IS USED FOR INITIALIZING THE VARIABLES AS WELL
478 C      AS INITIAL MESSAGES TO THE TERMINAL AND OUTPUT REPORT FILE.
479 C
480 C      SUBROUTINE INITIALZ
481 C
482 C
483 C      INTEGER      DAYTIME( 2 ), DDMMYY( 3 ), HMMSS( 3 ), FC(14), DAY
484 C      REAL          KCROP, INTNSITY
485 C      CHARACTER*8   TYPENOW
486 C      COMMON /BLOCK/
487 C      & SATHC, SUCTION, SFPROS, RTPROS, SFFC, RTFC, SFUP,
488 C      & SW, SFUC, RTUC, KCROP,
489 C      & DAY, RAIN, DUR, INTNSITY, SLOPE, TYPENOW
490 C      COMMON /FILCOD/ FC
491 C
492 C
493 C      ENTRY COMMENCE
494 C      -----
495 C
496 C      AT THE BEGINING WRITE OUT A MESSAGE TO THE TERMINAL AND
497 C      GET A SEED FOR RANDOM NUMBER GENERATOR FUNCTIONS BASED
498 C      ON THE COMPUTER CLOCK
499 C
500 C      CALL DATE( DDMMYY )
501 C      CALL TIME( HMMSS )
502 C      CALL JDATE( DAYTIME )
503 C      WRITE(11,101) HMMSS, DDMMYY
504 C      WRITE(13,101) HMMSS, DDMMYY
505 C      PRIMNO = DAYTIME( 2 )
506 C      CALL IRANP( PRIMNO )
507 C      RETURN
508 C
509 C
510 C
511 C      ENTRY DAWN
512 C      -----
513 C
514 C      THIS ENTRY INITIALIZES THE MOISTURE CONTENT OF A CELL
515 C
516 C      SW = 0
517 C      DAY = 0
518 C      SFUC = SFFC
519 C      RTUC = RTFC
520 C      RETURN
521 C
522 C      101  FORMAT(/// TIME: '3A3,' , DATE: '3A3)
523 C      END

```

ORIGINAL PAGE 18
OF POOR QUALITY

```

524 C
525 C
526 C-----EVAPORAT
527 C
528 C THIS ROUTINE SIMULATES THE EVAPOTRANSPIRATION ON A GIVEN
529 C DAY BASED ON THE DATA GATHERED. BARE SOIL, CANOPY COVERED
530 C OR WATER COVERED CELLS ARE EACH TREATED DIFFERENTLY.
531 C
532 C SUBROUTINE EVAPORAT
533 C
534 C PARAMETER ( NSDAY= 24 )
535 C
536 C INTEGER FC( 14 ), DAY
537 C REAL ET0( NSDAY ), MR, KSOIL, KSTORM, KSWEVAP, KCROP, INTNSITY
538 C REAL A( NSDAY ), B( NSDAY ), C( NSDAY ), D( NSDAY )
539 C LOGICAL FRSTCALL
540 C CHARACTER*8 TYPENOW
541 C COMMON /DATA/ SWINF,RAININF,RTINF,SURUNOFF,RECHRG,SWEVAP,SFEVAP,
542 C & RTEVAP
543 C COMMON /BLOCK/
544 C & SATHC, SUCTION, SFPROS, RTPROS, SFFC, RTFC, SFUP,
545 C & SU, SFUC, RTUC, KCROP,
546 C & DAY, RAIN, DUR, INTNSITY, SLOPE, TYPENOW
547 C COMMON /FILCOD/ FC
548 C DATA FRSTCALL/ .TRUE. /
549 C DATA ET0 / 0.48, 0.22, 0.31, 0.48, 0.61, 0.58, 0.40, 0.46,
550 C & 0.28, 0.27, 0.23, 0.15, 0.25, 0.25, 0.43, 0.33,
551 C & 0.38, 0.28, 0.31, 0.31, 0.40, 0.68, 0.55, 0.59 /
552 C
553 C IF( FRSTCALL ) THEN
554 C FRSTCALL = .FALSE.
555 C
556 C COMPUTE THE CONSTANTST FOR KSOIL'S POLYNOMIAL EQUATIONS
557 C
558 C FOR IDAY=1, NSDAY
559 C A( IDAY ) = -0.05 + 0.732 / ET0( IDAY )
560 C B( IDAY ) = 4.97 - 0.661 * ET0( IDAY )
561 C C( IDAY ) = -8.57 + 1.560 * ET0( IDAY )
562 C D( IDAY ) = 4.35 - 0.880 * ET0( IDAY )
563 C END FOR
564 C END IF
565 C
566 C PE = ET0( DAY )
567 C KSTORM = (24 - DUR) / 24.0
568 C
569 C IF THE GROUND CELL IS A CANOPY THEN COMPUTE EVATRANSPIRATION
570 C 30% FROM SURFACE LAYER AND 70% FROM ROOT ZONE
571 C
572 C IF( TYPENOW .EQ. 'CANOPY ' ) THEN
573 C EVAP = PE * KCROP * KSTORM
574 C SFEVAP = AMIN1( SFUC*5 , 0.30*EVAP )
575 C RTEVAP = AMIN1( RTUC*95 , 0.70*EVAP )
576 C SFUC = SFUC - SFEVAP/5
577 C RTUC = RTUC - RTEVAP/95
578 C IF( SU .GT. 0 ) THEN
579 C SWINF = AMIN1( SU , SFEVAP )
580 C SU = SU - SWINF
581 C SFUC = SFUC + SWINF/5
582 C END IF
583 C RETURN
584 C END IF
585 C
586 C IF THIS CELL IS COVERED BY STANDING WATER THEN COMPUTE
587 C EVAPORATION OF STANDING WATER
588 C
589 C KSWEVAP = 1
590 C IF( SW .GT. 0 ) THEN
591 C EVAP = PE * KSTORM
592 C SWEVAP = AMIN1 ( SW , EVAP )

```

ORIGINAL PAGE IS
OF POOR QUALITY

```

593      SW = SW - SUEVAP
594      KSUEVAP = ( PE - SUEVAP ) / PE
595      PE = PE - SUEVAP
596      END IF
597 C
598 C      COMPUTE EVAPORATION FOR BARE SOIL
599 C
600      IF( PE .GT. 0 ) THEN
601      MR = ( SFUC - SFUP ) / ( SFEC - SFUP )
602      IF( MR .LT. 0 ) MR = 0
603      IF( MR .GT. 1 ) MR = 1
604      KSOIL = A(DAY) + B(DAY) * MR + C(DAY) * MR*MR +
605      & D(DAY) * MR*MR*MR
606      IF( KSOIL .LT. 0.05 ) KSOIL = 0.05
607      IF( KSOIL .GT. 1.00 ) KSOIL = 1.00
608      SFEVAP = PE * KSOIL * KSTORM * KSUEVAP
609      SFEVAP = AMIN( SFUC*5 , SFEVAP )
610      SFUC = SFUC - SFEVAP/5
611      END IF
612 C
613      RETURN
614      END

```


ORIGINAL PAGE 19
OF POOR QUALITY

```

615 C
616 C
617 C-----CELLDATA
618 C
619 C
620 C      THIS SOUBROUTINE GETS ALL THE AVAILABLE AND NECESSARY
621 C      INFORMATION ABOUT THE REQUESTED DATA BASE CELL.
622 C
623 C
624 C      SUBROUTINE CELLDATA( RQUSTROW, RQUSTCOL, ELEV, SOIL, CATG,
625 C      &                SLOPE, TYPE, CROP, FIELD )
626 C      IMPLICIT INTEGER ( A - Z )
627 C      PARAMETER ( NCOL=1245, NFIELD=10 )
628 C      DIMENSION CROPCODE( 10 ), FC( 14 )
629 C      REAL      SLOPE, RESFEET
630 C      CHARACTER*8 TYPE
631 C      LOGICAL FRSTCALL
632 C      COMMON /BUF1/ SOILS( NCOL ), ELEVS( NCOL ), CATGS( NCOL )
633 C      SPECIAL COMMON BUF1
634 C      COMMON /FILCOD/ FC
635 C      DATA RESFEET/ 328.08 /
636 C      DATA CURNTROW / 0 /, FRSTCALL/ .TRUE. /
637 C      DATA CROPCODE/ 3, 5, 5, 4, 4, 3, 2, 2, 1, 6/
638 C      1-ALFALFA, 2-SOYBEAN, 3-WHEAT & OATS, 4-CORN, 5-SORGHUM, 6-PASTURE
639 C
640 C
641 C
642 C      WHEN CALLED FOR THE FIRST TIME OPEN ALL INPUT & OUTPUT FILES
643 C
644 C      IF( FRSTCALL ) THEN
645 C      CALL GETFILES
646 C      FRSTCALL = .FALSE.
647 C      END IF
648 C
649 C      IF THE ROW WHICH CONTAINS THE REQUESTED CELL IS NOT READ
650 C      YET, READ THE NEXT RECORD OF ALL THREE DATA BASE MAPS.
651 C
652 C      IF( CURNTROW .LT. RQUSTROW ) THEN
653 C      CURNTROW = CURNTROW + 1
654 C      CALL READREC( FC(2), SOILS, NCOL )
655 C      CALL READREC( FC(3), ELEVS, NCOL )
656 C      CALL READREC( FC(4), CATGS, NCOL )
657 C      END IF
658 C
659 C      THE ROW WHICH CONTAINS THE REQUESTED CELL IS IN THE MEMORY
660 C      EXTRACT NECESSARY INFORMATION.
661 C
662 C      ELEV = ELEVS( RQUSTCOL )
663 C      SOIL = SOILS( RQUSTCOL )
664 C      CATG = CATGS( RQUSTCOL )
665 C
666 C      IF( RQUSTCOL .NE. NCOL ) THEN
667 C      NEXTELEV = ELEVS( RQUSTCOL+1 )
668 C      ELSE
669 C      NEXTELEV = ELEVS( RQUSTCOL-1 )
670 C      END IF
671 C      SLOPE = ATAN( REAL( ELEV - NEXTELEV ) / RESFEET )
672 C      SLOPE = ABS( SLOPE ) * 57.2958
673 C
674 C      DETERMINE THE SOIL TYPE FROM SOIL MAP CODES
675 C
676 C      SOIL = SOIL / 30
677 C
678 C      DETERMINE THE TYPE OF THE CATEGORY (NON-AGRICULTURAL ,
679 C      BRAE SOIL OR CROP). IF IT IS A CROP TYPE FIND CROP.
680 C
681 C      IF( (CATG .GE. 230) .OR. (CATG .LE. 50) ) THEN
682 C      TYPE = 'NONAGRIC'
683 C      ELSE IF( (CATG .LT. 230) .AND. (CATG .GT. 150) ) THEN
684 C      TYPE = 'BARESOIL'

```

ORIGINAL PAGE IS
OF POOR QUALITY

```
685 ELSE IF( (CATG .GE. 50 ) .AND. (CATG .LE. 150) ) THEN
686 TYPE = 'CROP'
687 IC = CATG / 10 - 5
688 CROP = CROPCODE( IC )
689 FIELD = MOD( CATG , (CATG/10 * 10 ) ) + 1
690 CATG = CATG /10 * 10
691 END IF
692 C
693 C
694 RETURN
695 END
```

ORIGINAL PAGE IS
OF POOR QUALITY

```

696 C
697 C
698 C-----CROPDATA
699 C
700 C
701 C      THIS ROUTINE FINDS MORE INFORMATION ABOUT A CELL WHICH IS
702 C      REGISTERED AS CROP, SUCH AS CROP'S PLANTING DATE, CROP
703 C      CONSTANT K, AND ITS DYNAMIC TYPE BASED ON THE CROP CALANDER.
704 C
705 C
706 C      SUBROUTINE CROPDATA( CROP, FIELD, DATE, KCROP, TYPENOW )
707 C
708 C      PARAMETER ( NCROP=6 , NFIELD=10 , NSTG=5 )
709 C      IMPLICIT INTEGER ( A - Z )
710 C      DIMENSION PDATES( NCROP,NFIELD ), STAGEDAY( NCROP,NSTG )
711 C      REAL      KEQCONST( NCROP, NSTG, 2), M, A, KCROP
712 C      INTEGER   FC( 14 )
713 C      CHARACTER*8 TYPENOW
714 C      COMMON /FILCOD/ FC
715 C
716 C      DATA (( PDATES( IC , IF ), IF=1, NFIELD), IC=1, NCROP)
717 C      1-ALFALFA,2-SOYBEANS,3-WHEAT & OATS,4-CORN,5-SORGHUM,6-PASTURE
718 C      & / 62, 66, 69, 73, 71, 75, 78, 82, 87, 93,
719 C      & 126, 134, 142, 149, 155, 158, 162, 167, 173, 186,
720 C      & 54, 59, 62, 65, 68, 70, 74, 79, 84, 93,
721 C      & 107, 112, 117, 122, 127, 130, 135, 142, 149, 161,
722 C      & 120, 129, 134, 138, 143, 149, 155, 161, 169, 181,
723 C      & 73, 73, 73, 73, 73, 73, 73, 73, 73, 73 /
724 C
725 C      DATA ((STAGEDAY( IC, IS ), IS=1, NSTG), IC=1, NCROP)
726 C      & / 20, 61, 183, 217, 365,
727 C      & 19, 49, 102, 139, 365,
728 C      & 31, 67, 105, 117, 365,
729 C      & 31, 72, 122, 166, 365,
730 C      & 28, 68, 112, 140, 365,
731 C      & 20, 61, 183, 217, 365 /
732 C
733 C      DATA ((( KEQCONST( IC,IS,IK), IK=1,2), IS=1,NSTG), IC=1,NCROP)
734 C      & / 0.0 , 0.7 , 0.004, 0.627, 0.0 , 0.85 ,
735 C      & -0.01 , 2.7 , 0.0 , 0.5 ,
736 C      & 0.0 , 0.7 , 0.012, 0.478, 0.0 , 1.05 ,
737 C      & -0.016, 2.7 , 0.0 , 0.45 ,
738 C      & 0.0 , 0.7 , 0.011, 0.356, 0.0 , 1.1 ,
739 C      & -0.071, 8.54 , 0.0 , 0.25 ,
740 C      & 0.0 , 0.7 , 0.010, 0.398, 0.0 , 1.1 ,
741 C      & -0.013, 2.625, 0.0 , 0.55 ,
742 C      & 0.0 , 0.7 , 0.009, 0.455, 0.0 , 1.05 ,
743 C      & -0.020, 3.25 , 0.0 , 0.5 ,
744 C      & 0.0 , 0.7 , 0.001, 0.68 , 0.0 , 0.75 ,
745 C      & -0.007, 2.1 , 0.0 , 0.5 /
746 C
747 C
748 C
749 C      PLNTDATE = PDATES ( CROP , FIELD )
750 C      CROPCNT = DATE - PLNTDATE
751 C
752 C      DETERMINE THE STAGE OF THIS CROP SUCH AS EMERGED, HARVESTED, ...
753 C
754 C      FOR STAGE=1, 5
755 C      IF( CROPCNT .LT. STAGEDAY( CROP, STAGE ) ) GOTO 10
756 C      END FOR
757 C      10 M = KEQCONST( CROP, STAGE, 1 )
758 C      A = KEQCONST( CROP, STAGE, 2 )
759 C      KCROP = A + M * CROPCNT
760 C
761 C      TREAT ALL AS MEDIUM ROUGH BARE BEFOR EMERGENCE
762 C
763 C      IF( STAGE .LT. 2 ) THEN
764 C      TYPENOW = 'MEDMBARE'
765 C      RETURN

```

ORIGINAL PAGE IS
OF POOR QUALITY

```
766      END IF
767 C
768 C      IF CROP STAGE IS AFTER EMERGENCE AND BEFOR HARVEST
769 C      THEN TREAT IT AS A CANOPY
770 C
771      IF( STAGE .LT. 5 ) THEN
772      TYPENOW = 'CANOPY'
773      RETURN
774      END IF
775 C
776 C      AFTER HARVEST TREAT WHEAT, OATS AND ALFALFA AS SMOOTH BARE
777 C      AND TREAT ALL OTHERS AS MEDIUM ROUGH BARE
778 C
779      IF( (CROP .EQ. 1) .OR. (CROP .EQ. 3) ) THEN
780      TYPENOW = 'SMTHBARE'
781      ELSE
782      TYPENOW = 'MEDMBARE'
783      END IF
784 C
785      RETURN
786      END
```

ORIGINAL PAGE IS
OF POOR QUALITY

```

787 C
788 C
789 C-----SOILDATA
790 C
791 C
792 C      THIS ROUTINE FINDS THE BULK DENSITY OF THE GIVEN SOIL
793 C      BASED ON THE BULK DENSITY DISTRIBUTION WITHIN THAT
794 C      SOIL, AND RETURNS OTHER REQUIRED INFORMATION ABOUT THE GIVE
795 C      SOIL SUCH AS WILTING POINT WATER CONTENT, FIELD CAPACITY
796 C      WATER CONTENT, HYDRAULIC CONDUCTIVITY AT SATURATION, ETC.
797 C
798 C      SUBROUTINE SOILDATA( SOIL, SFPROS, RTPROS, SFFC, RTFC,
799 C      & SFWP, SATHC, SUCTION )
800 C
801 C
802 C      IMPLICIT INTEGER ( A - Z )
803 C
804 C      PARAMETER ( NSOIL= 8 , NBD= 15 )
805 C      REAL SFBULK(NBD), B(NSOIL), FSUCTION(NSOIL), ALFA(NSOIL)
806 C      REAL RTBULK( NBD ), SSUCTION( NSOIL ), SHYDCOND( NSOIL )
807 C      REAL SFPROS, SATHC, SUCTION, SATSUCT, SFWP, SFFC, RTFC
808 C      REAL RTPROS, FBD, RTBD
809 C      LOGICAL FRSTCALL
810 C      COMMON /BUF2/ PROBABIL( NSOIL , 100 ), PERCENTS( NSOIL ,NBD )
811 C      SPECIAL COMMON BUF2
812 C
813 C      DATA ((PERCENTS( IS , IBD), IBD=1, NBD), IS=1, NSOIL)
814 C      & / 0, 0, 0, 0, 0, 7, 7, 22, 22, 14, 14, 14, 0, 0, 0,
815 C      & 0, 0, 0, 11, 26, 26, 26, 11, 0, 0, 0, 0, 0, 0, 0,
816 C      & 2, 3, 3, 8, 18, 20, 17, 11, 12, 3, 3, 0, 0, 0, 0,
817 C      & 0, 0, 1, 9, 22, 25, 14, 11, 9, 5, 2, 2, 0, 0, 0,
818 C      & 0, 0, 0, 18, 18, 28, 18, 18, 0, 0, 0, 0, 0, 0, 0,
819 C      & 1, 1, 1, 7, 18, 22, 23, 15, 7, 4, 1, 0, 0, 0, 0,
820 C      & 0, 0, 0, 7, 19, 18, 30, 15, 7, 4, 0, 0, 0, 0, 0,
821 C      & 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 15, 31, 23, 8, 15, 8 /
822 C
823 C      DATA SFBULK/ 0.818, 0.888, 0.957, 1.03, 1.10, 1.17, 1.24, 1.30,
824 C      & 1.37 , 1.44 , 1.51 , 1.58, 1.65, 1.72, 1.79 /
825 C      DATA RTBULK/ 1.10, 1.15, 1.20, 1.25, 1.30, 1.35, 1.40, 1.45,
826 C      & 1.50, 1.55, 1.60, 1.65, 1.70, 1.75, 1.80 /
827 C
828 C      DATA B
829 C      & / 9.77, 6.66, 7.21, 6.81, 6.22, 6.81, 6.66, 4.26 /
830 C      DATA FSUCTION
831 C      & / 22.49, 13.91, 12.90, 13.18, 16.03, 13.18, 13.91, 3.22 /
832 C      DATA SSUCTION
833 C      & / 31.20, 34.67, 30.76, 33.08, 39.25, 33.08, 34.67, 10.14 /
834 C      DATA SHYDCOND
835 C      & / 0.814, 2.33, 2.02, 2.31, 2.39, 2.31, 2.33, 58.36 /
836 C      DATA FRSTCALL/ .TRUE. /
837 C
838 C
839 C      SET UP THE PROBABILITY ARRAY FOR BULK DENSITY DETERMINATION
840 C      OF EACH SOIL TYPE. (ONLY AT FIRST CALL)
841 C
842 C      IF( FRSTCALL ) THEN
843 C      FRSTCALL = .FALSE.
844 C      FOR IS=1, NSOIL
845 C      ALFA( IS ) = 1 / B( IS )
846 C      END FOR
847 C      FOR IS=1, NSOIL
848 C      START = 1
849 C      STOP = 0
850 C      FOR BDCODE=1, NBD
851 C      PERC = PERCENTS( IS , BDCODE )
852 C      IF( PERC .NE. 0 ) THEN
853 C      STOP = STOP + PERC
854 C      FOR I=START, STOP
855 C      PROBABIL( IS, I ) = BDCODE
856 C      END FOR

```

ORIGINAL PAGE IS
OF POOR QUALITY

```

857      START = START + PERC
858      END IF
859      END FOR
860      IF( STOP .NE. 100 ) WRITE(11, '(1X, 'STOP-', I4, I6)') STOP, IS
861      END FOR
862      END IF
863 C
864 C      GET THE BULK DENSITY ACCORDING TO THE PROBABILTY FOR THIS SOIL
865 C      FOR BOTH SURFACE LAYER (0-5 CM) AND ROOT LAYER (5-95 CM)
866 C
867      RANDOM = IRAN( 1 , 100 )
868      BDCODE = PROBABIL( SOIL, RANDOM )
869      SFBD = SFBULK( BDCODE )
870      RTBD = RTBULK( BDCODE )
871 C
872 C      CALCULATE THE WATER CONTENT OF EACH SOIL TYPE AT WILTING POINT
873 C      AND FIELD CAPACITY. SPECIFIC BULK DENSITY IS 2.65 FOR ALL SOILS
874 C
875      SFPROS = 1 - SFBD / 2.65
876      RTPROS = 1 - RTBD / 2.65
877      SFFC = SFPROS * ( SSUCTION( SOIL ) / 333.0 ) ** ALFA( SOIL )
878      RTFC = RTPROS * ( SSUCTION( SOIL ) / 333.0 ) ** ALFA( SOIL )
879      SFWP = SFPROS * ( SSUCTION( SOIL ) / 15000 ) ** ALFA( SOIL )
880      SUCTION = FSUCTION( SOIL )
881      SATHC = SHYDCOND( SOIL )
882      RETURN
883      END

```

ORIGINAL PAGE IS
OF POOR QUALITY

```
884 C
885 C
886 C-----GETFILES
887 C
888 C      THIS ROUTINE OPENS ALL THE INPUT AND OUTPUT FILES AND
889 C      ASSIGNS AN AVAILABLE UNIT (FILECODE) ON WHICH THE FILE
890 C      WILL BE OPENED.
891 C
892 C      SUBROUTINE GETFILES
893 C
894 C      INTEGER&1  FILENAME( 17 )
895 C      INTEGER    FC( 14 ), ERRCODE
896 C      LOGICAL     ERR
897 C      COMMON /FILCOD/ FC
898 C
899 C
900 C      WRITE(11,104)
901 C      READ(12,102) FILENAME
902 C      CALL OPN( FC(1), FILENAME, 'OLD', 'FOR', ERRCODE, ERR )
903 C      IF( ERR ) THEN
904 C      WRITE(11,101) FILENAME, ERRCODE
905 C      STOP
906 C      END IF
907 C      READ(FC(1),&) NUMFILES
908 C      FOR I=2,NUMFILES+1
909 C      READ(FC(I),102) FILENAME
910 C      CALL OPN(FC(I),FILENAME, 'OLD', 'UNF', ERRCODE, ERR)
911 C      IF( ERR ) THEN
912 C      WRITE(11,101) FILENAME, ERRCODE
913 C      STOP
914 C      END IF
915 C      WRITE(11,103) FILENAME, FC(I)
916 C      END FOR
917 C      RETURN
918 101  FORMAT(1X, 'ERROR *** WHILE OPENING '17A1, 'ERRCODE='13)
919 102  FORMAT(17A1)
920 103  FORMAT(1X,17A1, 'WAS ASSIGNED TO'14)
921 104  FORMAT(1X, 'ENTER NAME OF THE FILE WHICH CONTAINS INPUT',
922 C      & ' AND OUTPUT FILE NAMES')
923 C      END
```

ORIGINAL PAGE IS
OF POOR QUALITY

```

924 C
925 C
926 C-----IOCALLS
927 C
928 C
929 C      THIS ROUTINE HAS TWO ENTRIES USED IN READING AND WRITING
930 C      FROM AND TO THE I/O FILES
931 C
932 C      SUBROUTINE IOCALLS
933 C
934 C      IMPLICIT INTEGER ( A - Z )
935 C      PARAMETER ( NWRD =1245 , NPAUSE=3 )
936 C      DIMENSION RECORD( NWRD ), MATRIX( NPAUSE, NWRD )
937 C      INTEGER FC( 14 )
938 C      COMMON /FILCOD/ FC
939 C
940 C
941 C
942 C      ENTRY READREC ( FILECODE, RECORD, NUWORDS )
943 C      -----
944 C      BUFFER IN ( FILECODE, RECORD, B, NUWORDS, IO )
945 C      CALL STATUS( FILECODE )
946 C      IF( IO .NE. 2 ) THEN
947 C      WRITE(11,101) FILECODE, IO
948 C      STOP
949 C      END IF
950 C      RETURN
951 C
952 C
953 C      ENTRY WRITDATA ( IDENT , MATRIX, NCOL )
954 C      -----
955 C
956 C      IF( IDENT .EQ. 1 ) OTFILE=FC(6)
957 C      IF( IDENT .EQ. 2 ) OTFILE=FC(10)
958 C      FOR IP=1, NPAUSE
959 C      FOR COL=1, NCOL
960 C      RECORD( COL ) = MATRIX( IP , COL )
961 C      END FOR
962 C      BUFFER OUT( OTFILE, RECORD, B, NCOL, IO )
963 C      CALL STATUS( OTFILE )
964 C      IF( IO .NE. 2 ) THEN
965 C      WRITE(11,102) OTFILE, IO
966 C      STOP
967 C      END IF
968 C      OTFILE = OTFILE + 1
969 C      END FOR
970 C      RETURN
971 C
972 101 FORMAT(1X,'ERROR *** WHILE READING FROM UNIT 'I4,' STATUS',I4)
973 102 FORMAT(1X,'ERROR *** WHILE WRITING TO UNIT 'I4,' STATUS',I4)
974 C      END

```


ORIGINAL PAGE IS
OF POOR QUALITY

```
975 C
976 C
977 C-----UPDTHIST
978 C
979 C
980 C      THIS ROUTINE 'UPDATES THE HISTOGRAMS
981 C
982 C      SUBROUTINE UPDTHIST( VAL, HIST, INDEX, MIN, MAX )
983 C      IMPLICIT INTEGER ( A - Z )
984 C      PARAMETER ( NPAUSE=3 )
985 C      DIMENSION HIST( NPAUSE, MAX )
986 C
987 C
988 C      UPDATE MIN, MAX VALUES OF DATA
989 C
990 C      HIST( INDEX , 1 ) = MIN0( HIST( INDEX , 1 ) , VAL )
991 C      HIST( INDEX , MAX-MIN+5 ) = MAX0( HIST( INDEX , MAX-MIN+5 ), VAL )
992 C
993 C      UPDATE THE TOTAL NUMBER OF VALUES COUNTED
994 C
995 C      HIST( INDEX , MAX-MIN+6 ) = HIST( INDEX, MAX-MIN+6 )+1
996 C
997 C      UPDATE THE FREQUENCY COUNT FOR THIS VALUE
998 C
999 C      VAL = MAX0( MIN0( MAX+1 , VAL ), MIN-1 )
1000 C      HIST( INDEX, VAL-MIN+3 ) = HIST( INDEX, VAL-MIN+3 ) + 1
1001 C      RETURN
1002 C      END
)
```

ORIGINAL PAGE IS
OF POOR QUALITY

```

1003 C
1004 C
1005 C-----OTPTHIST
1006 C
1007 C
1008 C      THIS ROUTINE TAKES A GIVEN HISTOGRAM ARRAY CONTAINING THE
1009 C      FREQUENCIES AND WRITES OUT THE PERCENTS AND CUMULATIVE
1010 C      PERCENTS FOR EACH DATA VALUE.
1011 C
1012 C      SUBROUTINE OTPTHIST( HIST, INDEX, MIN, MAX )
1013 C
1014 C      IMPLICIT INTEGER ( A - Z )
1015 C      DIMENSION HIST( 3, MAX )
1016 C      REAL TOTAL, SUM
1017 C
1018 C
1019 C      TOTAL = HIST ( INDEX , MAX-MIN+6 )
1020 C      SUM = HIST( INDEX , 2 )
1021 C
1022 C      WRITE OUT INFORMATION ON DATA POINTS ENCOUNTERED WHICH
1023 C      WERE LESS THAN THE INDICATED MINIMUM VALUE
1024 C
1025 C      WRITE(13,100) MIN, HIST( INDEX, 2 ), SUM/TOTAL, SUM/TOTAL
1026 C
1027 C      WRITE OUT PERCENTS AND CUM PERCENTS FOR ALL VALUES FROM
1028 C      INDICATED MINIMUM VALUE THROUGH MAXIMUM VALUE
1029 C
1030 C      FOR PTR= 3, MAX-MIN+3
1031 C      COUNT = HIST( INDEX, PTR )
1032 C      SUM = SUM + COUNT
1033 C      IF( COUNT .NE. 0 ) THEN
1034 C      WRITE(13,101) MIN+PTR-3, COUNT, COUNT/TOTAL, SUM/TOTAL
1035 C      END IF
1036 C      END FOR
1037 C
1038 C      WRITE OUT INFORMATION ON DATA POINTS ENCOUNTERED WHICH
1039 C      WERE LARGER THAN THE INDICATED MINIMUM VALUE
1040 C
1041 C      COUNT = HIST( INDEX, MAX-MIN+4 )
1042 C      SUM = SUM + COUNT
1043 C      WRITE(13,102) MAX, COUNT, COUNT/TOTAL, SUM/TOTAL
1044 C
1045 C      WRITE OUT TOTAL NUMBER OF VALUES, MIN VALUE AND MAX VALUE
1046 C      THAT WAS ENCOUNTERED
1047 C
1048 C      WRITE(13,103) TOTAL, HIST( INDEX , 1 ), HIST( INDEX , MAX-MIN+5)
1049 C      RETURN
1050 C
1051 100  FORMAT(/5X,'RANGE',14X'COUNT',7X,'PERCENT'10X'CUM PERCENTS',
1052 & //5X,'<'17,5X,'-',5X,18,5XE14.7,5XE14.7)
1053 101  FORMAT(7X,16,5X,'-',5X,18,5XE14.7,5X,E14.7)
1054 102  FORMAT(5X,'>'17,5X,'-',5X,18,5XE14.7,5XE14.7)
1055 103  FORMAT(2X10.1,' TOTAL VALUES COUNTED'5X'MIN AND MAX VALUES'
1056 & ' ENCOUNTERED = '19,2X19)
1057 END

```

NASA-JSC